Republic of Iraq

Ministry of Higher Education and Scientific Research

University of Tikrit

College of Computer Science and Mathematics

Department of Computer Science

Evaluation and Selection Best Deep Learning Model Based on New Development for FDOSM

A Thesis Submitted to

The Council of the College of Computer Science and mathematics

University of Tikrit

In Partial Fulfillment of the Requirement for the Degree of Master of science in Computer

By

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2024 A.D. 1446 A.H.

بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

﴿وَعَلَّمَكَ مَا لَمْ تَكُنْ تَعْلَمُ وَكَانَ فَضْلُ اللَّهِ عَلَيْكَ عَظِيمًا﴾

(سورة النساء: 113)

الاهداء..

الى من برضاهما اقترنت الجنة . . رمزاً للحنان والعطاء الذي لا يعرف حدوداً . . والديّ الحبيبين . . شكراً لكم على كل لحظة دعم، على دعائكم وصلواتكم التي كانت وقوداً لروحي . . كل كلمات الحب والشكر لا تفيكم حقكم . .

إلى من جعله الله لي سكنا . . شريك حياتي وداعمي الأول . . وجودك بجانبي هو أعظم نعمة من الله . . زوجي الغالي

إلى نور حياتي ومن بهم تتعلق امنياتي . . قرة عيني وسعادتي . . اولادي

إلى مصدر قوتي وطمأنينة قلبي . . سندي في الحياة . . أخي وأخواتي

إلى والدا زوجي الغاليان، أشكركم من كل قلبي على حبكم ودعمكم . . بكم كانت الصعاب أهون، وبكم كانت الفرحة أكبر . .

الى من كانوا نعمة من الرب صديقات الدرب . . (ريم، معالم، إسراء، قبس، وصال) لقد كنتم النور الذي أضاء لي دربي في أوقات الظلام . . والدعامة التي استندت إليها في لحظات ضعفي . . شكراً لكم على دعمكم اللامتناهي ومساندتكم التي لا تقدر بثمن . .

الى من انارو لنا درب المعرفة وغرسوا فينا حب العلم . . اساتذتي الافاضل . .

اهدي لكم ثمرة جهدي هذا . . مستعينة بالله على قبوله . . واشكره اولا واخرآ على توفيقه . .

رشا عبد الله . .

Acknowledgments

Foremost, Praise be to God, who has made a destiny for everything. and prayers and peace be upon the best of creatures and human beings, our prophet Muhammad

And after...

My thanks and gratitude go to my honorable supervisor, Assistant Professor Dr. Mahmood Maher Salih, for his exceptional and distinguished role that accompanied the stages of the research, by proposing the research project, and the subsequent continuous creative effort to solve the problems throughout the duration of the study, My thanks go to the Deanship of the College of Computer Science and Mathematics - Tikrit University, with its teachers and employees, and the Department of Computer Science, represented by its head, Assistant Professor Dr. Muhammad Aktham Ahmed, and my honorable colleagues for their continued support.

My appreciation and gratitude to everyone who contributed to me with a word or a letter but was not mentioned by my pen, and I ask God Almighty to guide me and them to what He loves and is pleased with.

Rasha Abdullah

Abstract

In recent years, deep learning has significantly advanced various domains such as healthcare, education, and economics as it can produce high-performance results by its ability to accurately interpret the data including image classification, object detection and many more. The success of deep learning applications is heavily dependent on selecting the most appropriate model, as this choice impacts the accuracy, efficiency, and reliability of the results. However, selecting the best deep learning model become increasingly complex due to the varying nature of data and the multiple evaluation metrics. To address this challenge, Multi-Criteria Decision-Making (MCDM) methods have emerged as essential tools for selecting the most suitable model for specific tasks. So, the latest method, namely, the fuzzy decision by opinion score method (FDOSM), has efficiently been able to solve some existing issues that other methods could not manage to solve. Yet, several problems still exist in the FDOSM and its extensions, such as uncertainty. In this paper, the FDOSM is extended into Heptagonal -FDOSM to solve this problem. This extension allows and provide for a more accurate representation of expert opinions and performance metrics. As a result, our study's methodology is divided into two phases: the first is to create a decision matrix including a combination of 10 evaluation criteria plus ten DL models. The second phase is extending FDOSM into the Heptagonal environment to address the uncertainty issues that FDOSM facing. The study results revealed the following: for the individual decision-maker, the best alternative for first Expert was "Xception" with score of "1.44". While (ResNet-101) is the best alternative to the second and third experts, with scores of "1.051429, 0.857143", respectively, on the other hand, the best DL model based on the group decision making is "ResNet-101" which is the best among all the used models, with score, "1.12" this final rank is more logical and nearest to decision makers' opinion. Finally, objective validation and comparative analysis was conducted.

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LIST OF ABBREVIATIONS

AI	Artificial intelligence
ANNs	Artificial neural networks
AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
BWM	Best – Worst Method
DL	Deep Learning
DNNs	Deep neural networks
DTL	Deep transfer learning
FWZIC	Fuzzy-weighted zero-inconsistency
FDOSM	Fuzzy Decision by Opinion Score Method
HFN	Heptagonal Fuzzy Number
LDM	linguistic decision matrix
ML	Machine Learning
MCDM	Multi Criteria Decision Making
SAW	Simple Additive Weighting
TrFN	Trapezoidal Fuzzy Number
TFN	Triangular fuzzy numbers
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VIKOR	VlseKriterijumska Optimizacija I Kompromisno Resenje

Chapter One: Introduction

1.1 Introduction

This chapter provides a concise overview of the research, research objectives, the problem statement, and the scope of research. Section (1.2), presents a brief background about research; section (1.3), presents the problem statement. Sections (1.4) and (1.5), present the research objectives and the research scope, respectively, finally, the outline of thesis will be presented in (1.6).

1.2 Research Background

Artificial intelligence (AI) refers to building machines as intelligent as the human brain. In computer science, AI refers to the study of "intelligent agents": any technology that understands its environment and performs actions that optimize its chances of success in achieving its goals. Machines must be capable of learning, so machine learning (ML) is a branch of AI [1, 2]. (ML) has become increasingly popular in studies and has been incorporated into various applications such as healthcare, financial services, vehicle automation, and retail.

Recently, Digital data has been formed in huge amounts and varieties, which requires solving how to use this data effectively and efficiently, which is the real challenge rather than collecting only. So, machine learning systems have assisted businesses in managing, analyzing, and producing output from massive amounts of this data because they can recognize hidden patterns and identify consumer preferences to enhance business and raise market trends [3, 4]. ML enables computers to learn and develop independently, and it is considered a data analysis method and analytical model automation that leads to higher expectations for machines. So, deep learning (DL) is one of the most frequently used ML algorithms because it assists in recognizing, measuring, and classifying models in various image data [5, 6]. Deep learning is a step in the right direction.

It is subset of machine learning that use neural networks to mimic the structure and function of the human brain. Because these neural networks are capable of learning from unstructured data, they are extremely successful at handling complicated tasks such as picture and speech recognition [7]. Also, it enhances the use of available data more effectively and efficiently because it manages huge amounts of data [3]. Deep learning is based on artificial neural network systems (ANNs). These ANNs are continually learning algorithms, and the efficiency of training procedures can be enhanced by continuously increasing the amount of data. The efficiency is affected by increasing data amounts. The training process is referred to as deep since the number of neural network layers rises with time [8].

The convolutional neural network (CNN) is one of the most famous and widely utilized deep learning networks. Because of CNN, DL is quite trendy now[9]. CNNs have performed wonderfully well in recognition of images applications, reaching up-to-date results on a variety of benchmarks [10].
deep neural nets have been shown to out-perform traditional machine learning algorithms[11]. As well as, it has been demonstrated to produce state-of-the-art results on a variety of tasks in fields particularly in image classification and recognition [12], segmentation [13], object detection [14]. automatic speech recognition, natural language processing, audio recognition, discovering drugs and bioinformatics [11, 15, 16].

In the context of deep learning, when choosing the best deep learning models, such as AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, Xception, and ResNet-101 [17]. evaluation metrics play an essential part in MCDM because they offer a quantitative measure to evaluate the performance of numerous alternatives which serve the criteria that measure different aspects of a model's performance, enabling decision-makers to come up with informed choices by taking into account multiple criteria and evaluating the performance of different alternatives [18-20]. Several criteria have been considered, including: accuracy, BACC, precision, recall, Specificity, and F1 score, true negative (TN), true positive (TP), false negative (FN), and false positive (FP) [21, 22]. However, when evaluating and benchmarking Deep Learning models, taking the previously stated criteria into account resulted in the multi-criteria issue [23]. The proposed multicriteria problem occurs when the criteria include a trade-off, such as between the TP and FN criteria [24]. The Conflict criteria are another concern in the evaluation process [25].

All of this raised the question of deciding how to select the best value in general of these models by achieving a good harmony between variation in the values of benefits criteria (i.e., high TP and TN) with high importance priority and cost criteria (i.e., low FP and FN) with a lower priority during the evaluation process. Therefore, multi-criteria decision making is the most effective scheme to evaluate and benchmarking DL models, allowing for the selection of the right DL models.

Multi-criteria decision-making (MCDM) is a popular subject in expert systems and operations research [26]. The goal of MCDM is to use multiple methods to address multi-aspect problems and to deliver decision-makers with tools to assist in making better choices in the face of complex situations [27]. However, uncertainty, ambiguity, consistency problems, unnatural comparisons, normalisation and distance measurement are the MCDM issues and challenges. Furthermore, making decisions needs the use of the advice of professionals and experts [28, 29]. Because they use linguistic terms, decision-makers (experts) cannot calculate weights in real numbers. As a result, addressing these issues has become more difficult. So, MCDM is established in a fuzzy environment [30-32].

Zadeh [33] introduced the fuzzy set concept as a modeling instrument for complex systems by giving grades ranging from [0, 1] to multiple alternatives.

Since Zadeh's approach to fuzzy collection and fuzzy logic became used to characterize imprecision, uncertainty, and obscureness in a variety of fields. So, fuzzy set theory has proven effective in MCDM models as a language capable of dealing with uncertainty and ambiguity. Fuzzy sets give a theoretical framework for quantifying a form of uncertainty that is present in many decision-making [34, 35].

Therefore, one of the most recent MCDM method that introduced to address the MCDM problems is fuzzy decision by opinion score method (FDOSM) it is used for ranking alternatives in a fuzzy environment [36]. It is a powerful and successful method that was published in 2020 [37]. The basic idea of FDOSM is to solve the identified challenges that get by using the optimal solution and an opinion matrix [38]. The FDOSM provides logical decisions based on the opinions of experts [39, 40]. minimized the number of comparisons, provided fair and implicit understandable comparisons, prevented inconsistency, reduced vagueness and gave a minimum number of mathematical operations. Since its release, FDOSM has been applied to several studies that tackle a wide range of MCDM issues as a result, this method saves data while also making a responsible conclusion [41]. However, despite FDOSM's effectiveness in addressing a wide range of problems, it still struggles from the uncertainty issue as an open challenge created by the opinions of expert [42].

1.2 Problem Statement

Select the best deep learning model from a set of available models based on multi criteria is difficult, therefor, MCDM will use to address this issue. Despite FDOSM's strength in resolving many issues, this method still suffers from uncertainty issue resulting from expert opinions[43]. According to the literatures fuzzy set theory is one of the best solutions to deal with uncertainty [44]. As a result, many types of fuzzy numbers have been developed in order to reduce uncertainty problems. In this study, FDOSM is extended by employing heptagonal fuzzy numbers.

1.4 Research Objectives

1- Investigating and analysis existing academic literature related to FDOSM.
2- To Apply different deep learning models to create the decision matrix.
3- Extending FDOSM into a new development (heptagonal fuzzy number)
4- selecting the best deep learning model using heptagonal-FDOSM.
5- Validate the result of the new extension using objective validation.

1.5 Research Scope

1- Investigating academic researches relating to FDOSM only in databases.
2- Applied the new extension to evolution deep learning models.
3- applying FDOSM as method in this thesis.

1.6 The outline of thesis

In additional to the first chapter, the entire thesis is divided into the following four chapters:

Chapter Two: Literature Review

The following chapter contains information about Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL), as well as an examination of the methods for deep learning used in this thesis. It investigates two primary approaches to Multi-Criteria Decision-Making (MCDM) and presents an overview of related research in the MCDM area.

Chapter Three: Research Methodology

This chapter will be presenting the proposed methodology, discuss how extend FDOSM into Heptagonal-FDOSM.

<u>Chapter Four:</u> Results and Discussion

Presenting the result of Heptagonal-FDOSM and discuss the results.

<u>Chapter Five:</u> Conclusion and Future Studies

Presenting the conclusion of the study and gives recommendations for future works.

Chapter Two: Literature Review

2.1 Introduction

After reviewing the theoretical literature and previous studies on the subject of our research, this study shows the following clarifications: it will cover each of the following subjects in this chapter: (2.2) A general introduction to artificial intelligence is provided in this part. (2.3) This section explains machine learning, including its various forms. (2.4) this section, will discuss about deep learning, including its definition, applications, and characteristics. A brief description about (CNN) will provided in (2.5). In part (2.6) will inform the MCDM in depth, covering its stages, terms, and areas of application. In (2.7) explained the popular approach to decision-making, the mathematical approach and in section (2.8) human approach will be discussed. The part (2.9) introduces the FDOSM approach to solving MCDM problems. This section (2.10) this part is devoted to fuzzy sets and its types. (2.11) A critical analysis of previous studies created using the FDOSM method is offered to prove that this new kind of fuzzy number hasn't been used in any study.

2.2 Artificial Intelligent (AI)

The concept of creating machines with human-like intelligence can be traced back to numerous domains, including philosophy, fiction, imagination, computer science, electronics, and engineering inventions [45]. Alan Turing's intelligence test [46] is an important turning point in the area of AI, sixty years later, intelligent machines exceed humans in many categories, including learning [47], thanks to significant improvements in other technologies such as large data and processing power for computers [48]. The definition of AI states that "AI is the study of how to make machines perform things that human beings do better at the moment" accurately defines the concept of AI. the main components of AI are: (1) learning; (2) knowledge representation; (3) perception; (4) planning; (5)

action; and (6) communication [49]. AI can be defined as an artificial object or thing that possesses the ability to fulfill or exceed the requirements of the job to which it is assigned [50]. Artificial intelligence (AI) has several advantages and has been successfully implemented in a variety of industrial fields, including image classification, speech recognition, autonomous vehicles, computer vision, and so on [51].

The "classic" three stages of AI evolution based on its capability levels: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI)[50]. based on the system's "degree of intelligence" in comparing to a human [52]. ANI, also known as weak AI, is a type of artificial intelligence (AI) in which machines incorporates modern artificial intelligence technologies in a certain domain, such as voice recognition software (for example, Apple's Siri), chess playing, sales prediction, movie recommendations, translation of languages, and prediction of the weather [53]. The AGI, often known as strong AI, it is a theoretical concept that can accomplish autonomous goals and transfer learnings across multiple scenarios. AGI agents will have intelligence above human levels, could be leading to improvements in complicated challenges like human health and global warming [50]. it is creating machines that are capable of solving a variety of complex issues in various domains and control themselves autonomously, with their own ideas, worries, emotions, strengths, weaknesses, and attitude. This is still a major aim for AI, but it has proven challenging and elusive to accomplish. The artificial super intelligence (ASI) create machines that outperform humans' capabilities in a wide range of fields [49]. ASI is possibly the most precise form of AI since it can make discoveries in general, scientific, educational, creative, as well as social domains [50].

2.3 Machine Learning

Machine Learning is a subfield of (AI) that deals with the creation and execution of computer programs that learn from experience or from historical relationships and trends in the data for achieving the objective of modeling, control, or prediction, improving their procedures for better performance and acquiring "intelligence" with time. using statistical techniques that are not explicitly programmed [4]. these analytical models enable researchers, data scientists, engineers, and analysts to "produce accurate, repeatable decisions and results" and find "hidden insights".

Machine Learning is used in a variety of computing tasks where creating and programming explicit algorithms with high performance is difficult or impossible; for example, Financial Trading, Data Security, Healthcare, Marketing Personalization, Smart Cars [54-56]. the Machine Learning methods are classified into four categories:

2.3.1 supervised Machine Learning

the study of how machines create decisions according to what they have learned from labeled datasets, i.e. input and intended output pairings. It is divided into two categories: classification and regression [57]. which can be a binary and/or categorical response. supervised learning could be utilized for process data classification, such as errors classification (i.e TRUE, FALSE) or operating mode classification (i.e ON, OFF). Otherwise, regression models can be built for prediction and estimation if the output value is either a real or continuous result. For example, "price" and "predicting weather". Process monitoring, classification of faults and identification, are some of the main applications of the supervised machine learning method [58]. The supervised machine learning algorithms are the one that require external assistance. The input dataset is separated into two parts: train and test. The train dataset contains an output variable that must be predicted or categorized. Every algorithm is designed to learn patterns from the training dataset and use them to predict or classify data from the test dataset [4].

2.3.2 Unsupervised Machine Learning

This method focused with how machines learn basic structure in unlabeled datasets. It is divided into two categories: clustering and dimension reduction (Association) techniques [59]. Unsupervised learning methods are applied to data with no labels. The unsupervised learning method's main objective is to study the data and discover some hidden patterns among it [58].

2.3.3 Reinforcement Learning

This method learning of how to map from situations to actions in order for maximizing the scalar reward or reinforcement signal". It is a computational approach to learning from the output based on interactions with the environment [60]. Reinforcement learning is used often in robotics, games, and navigation. The algorithm uses reinforcement learning to understand which activities provide the largest rewards through trial and error. The agent (the learner or decision maker), the environment (all that is the agent interacts with), and actions (what the agent is able to do) are the three basic components of this type of learning. The goal is for the agent to select activities that maximize the predicted reward over a specified time period. By following an established policy, the agent can achieve the goal greatly faster. As a result, the aim of reinforcement learning is to learn about the best policy [16].

2.3.4 Semi-supervised machine learning

It is a hybrid of supervised and unsupervised machine learning techniques. Semi-supervised learning employs both labeled and unlabeled data for training, generally combining just a little amount of labeled data with a big amount of unlabeled data (since unlabeled data is less expensive and requires less effort to obtain). This kind of learning can be combined with methods like classification, regression, and prediction. Early examples include recognizing a person's face on a web cam [16]. Figure (2.1). shows the categories of machine learning and some of its tasks.

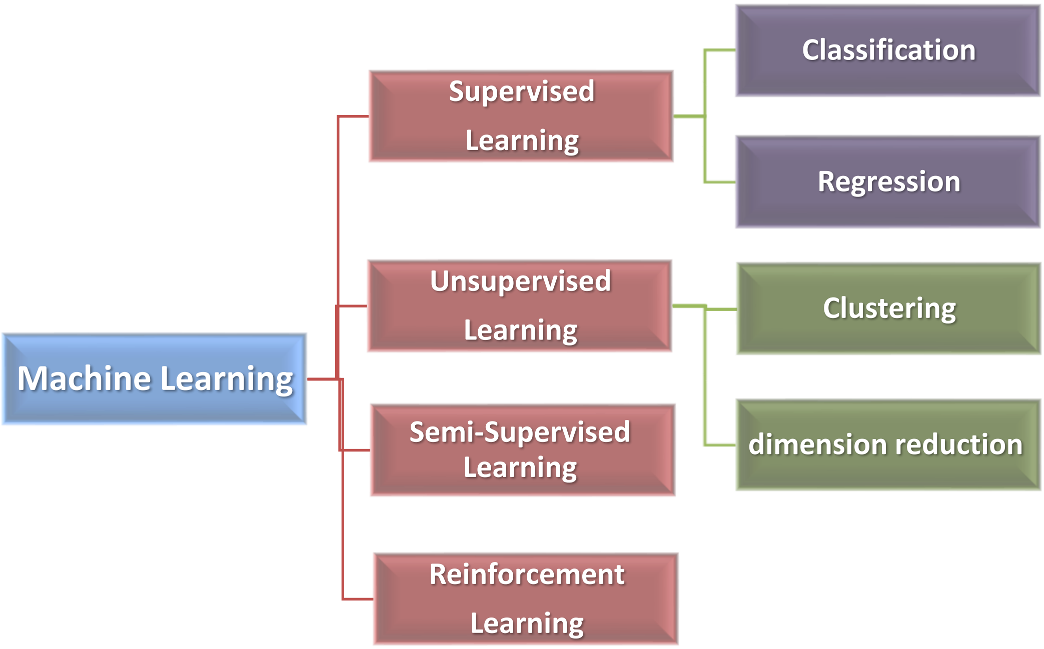


Figure 2.1. Categories of Machine Learning [61].

2.4 Deep Learning

Artificial neural networks (ANNs) are classified as "Traditional ANNs" or "Deep ANNs". ANNs are inspired by the operation of the human brain, emulating complicated processes such as pattern creation, thinking, learning, and making decisions [62]. The human brain is made up of billions of neurons that communicate with one another and process any information that is sent to them. Additionally, an ANN, which is a simplified model of the structure of a biological neural network, is made up of interconnected processing units that are organized in a certain topology. A variety of nodes, including the following, are placed in many layers:

- An input layer in which data is supplied into the system.
- One or more hidden layers in which learning occurs.
- An output layer in which the decision/prediction is made.

Figure (2.2). Comparison between ANNs and deep architectures. While ANNs are usually composed by three layers and one transformation toward the final outputs, deep learning architectures are constituted by several layers of neural networks.

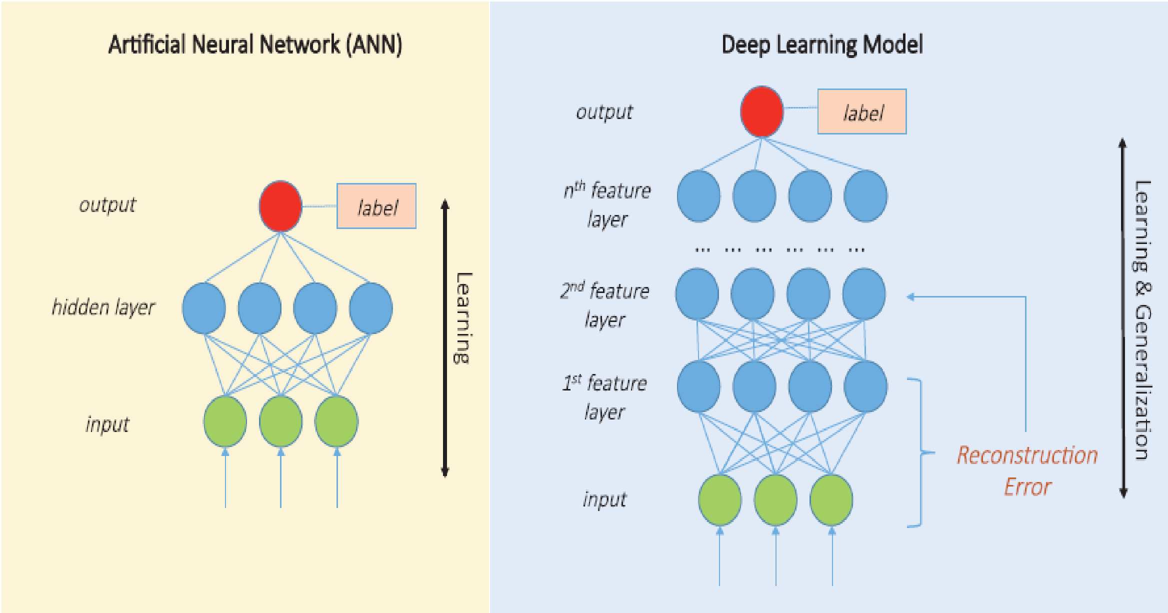


Figure 2.2. Comparison between ANNs and deep architectures [63].

Deep ANNs are also known as deep learning (DL) or deep neural networks (DNNs). They are a new area of ML research that allows computational models with several processing layers to learn complicated data representations at multiple levels of abstraction [2]. Lower layers learn basic features that are near the data input, while higher layers learn more sophisticated features derived from lower layer features. The architecture creates a powerful and hierarchical feature representation. It indicates that deep learning is well-suited for evaluating and extracting useful information from big amounts of data [1]. the effectiveness of training procedures can be enhanced by continuously increasing the amount of data. The greater the data amount, the greater the efficiency. The training process is referred to as deep since the number of neural network levels rises over time [15].

Deep learning has grown in popularity in recent years, so it is now widely used in various application yielding impressive results for object detection in images and speech recognition [64-66], natural language processing [67], translation[47]. below are the following deep learning characteristics [8]:

- Extremely useful tool in a wide range of fields.
- Have a high ability to learn.
- Has the ability to make better use of datasets.
- Learning how to extract features from data.
- Outperform humans in highly computational challenges.
- Deep learning requires very little manual engineering.
- Improved outcomes.
- deep learning networks is determined by the nature of network structure, activation function, and data representation.
- Prediction accuracy can be significantly enhanced.
- Finishing complex computational tasks.
- Better feature representation than a machine learning model.
- These networks can extract complex features using high-level abstraction.
- Strategies to good recognizing capability in the big data era.

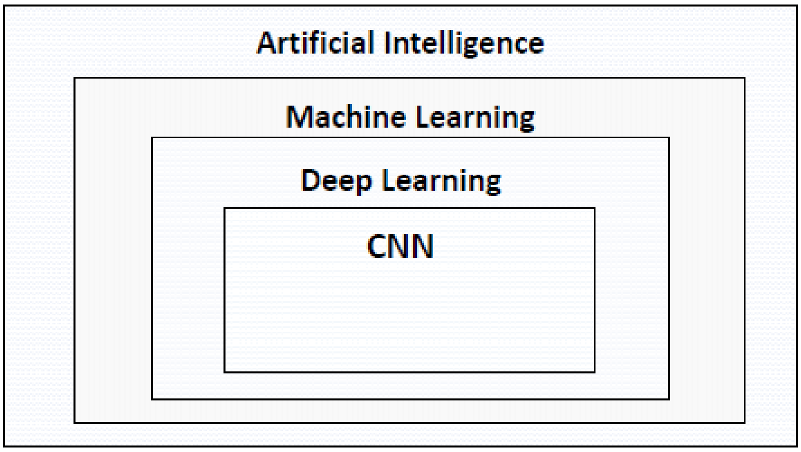


Figure 2.3. An illustration of the relationship between AI, ML, DL, and CNN[10].

2.5 Convolutional neural network (CNN)

The CNN is also known as ConvNet, it the most well-known and commonly used algorithm in the field of deep learning which is a subset of ML that resides under the general field of Artificial Intelligence, as shown in Figure (2.3). CNN's primary advantage over earlier versions is its ability to autonomously identify relevant features without supervision from humans [68]. This network is a multi-layer neural network with at least two hidden layers. CNN's hidden layers are made up of an ongoing series of convolutional layers. The convolutional layer is the main component of CNN. It extracts the incoming signal's high-level properties. Afterwards the convolution layer, the pooling layer is used. Pooling processes are configured depending on the application. The procedure of pooling is typically utilized to reduce dimensionality and choose the most important feature. The fully connected layer is the last layer belonging to the CNN framework, that can be either one or several layers. It comes after a sequence of convolution and pooling layers [69]. The CNN contains three dimensions: width, height, and depth. The height and width correlate to the black and white colors, while the depth relates to the red, green, and blue colors (RGB) through from where the image input is sent to the CNN layers [70, 71]. CNNs have become popular in a variety of applications, especially in the field of image recognition.

A quick summary of several different CNN architectures is provided below, each one having its own specific functions and characteristics. Ten pre-trained CNNs are utilized to distinguish between COVID-19 infection and non-infection as shown in figure (2.4).

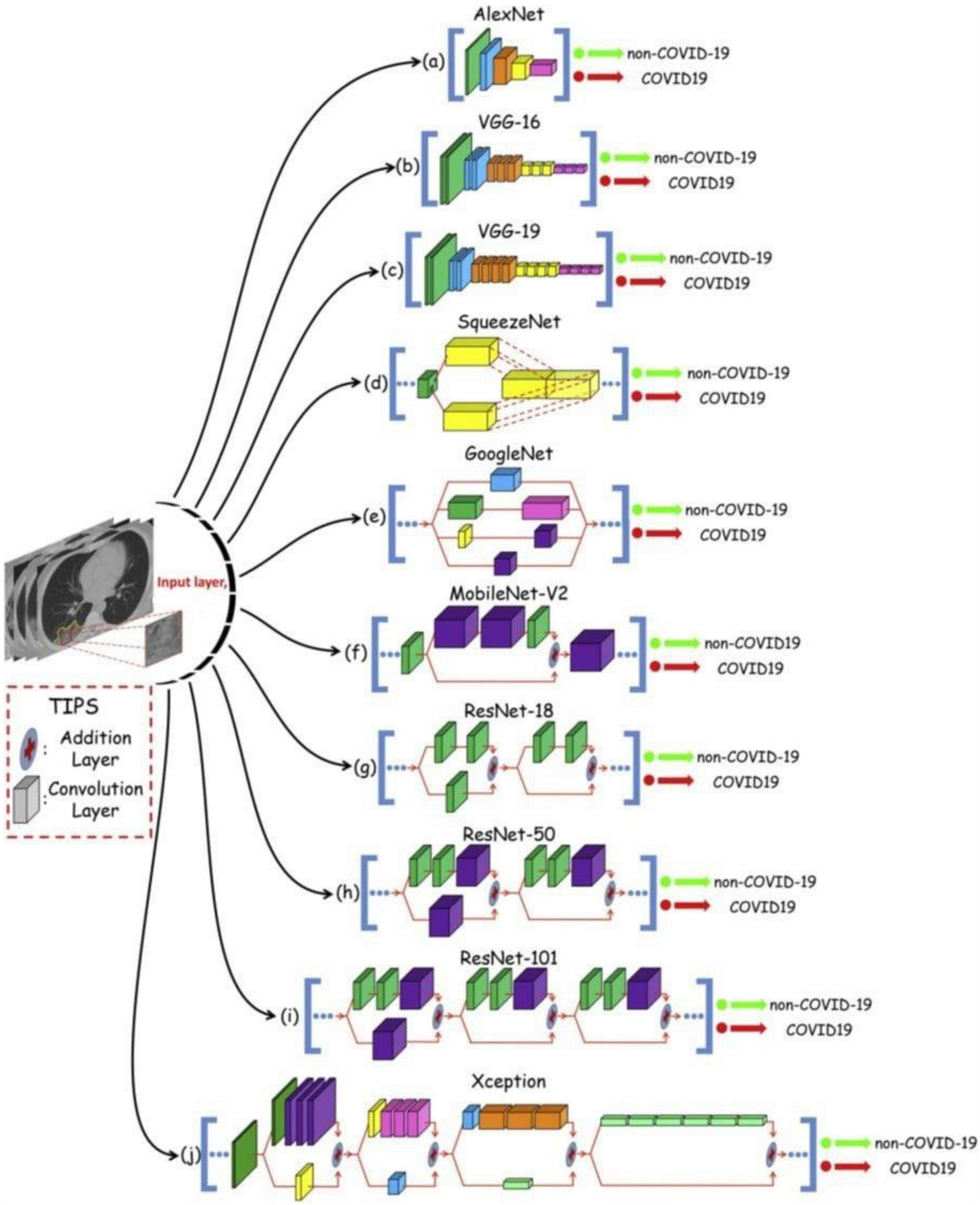


Figure 2.4. brief summary of the ten pre-trained network designs [72].

1. **Alex Net**

AlexNet is a CNN architecture developed by Alex Krizhevsky et al. in 2012. It obtained the highest possible efficiency on the ImageNet dataset[73, 74]. AlexNet has a simple eight-layer structure, including five convolutional layers and three fully linked layers. The CNN design is similar to LeNet's, except its deeper, with stacking convolutional layers along with additional filters. It is used to address difficult facial analysis tasks such as estimation of age and gender recognition, which means it can achieve excellent accuracy upon the most complex data sets. Its performance falls significantly if the convolutional layer is eliminated. It's the primary architecture used by every object retrieval activity. Deeper models, such as ResNet and GoogLeNet, beat AlexNet, but they are more computationally expensive[75].

2. **VGG Net**

The VGG model builds on the architecture of the AlexNet model, widening and deepening the network structure by extending the depth from 8 layers (AlexNet) to 16-19 various layers. The two variations of this architecture, VGG-16 and VGG-19, are named after the number of convolutional layers, which are 16 or 19. VGG16, as the name means, comprises 16 weighted layers (13 convolutional layers and 3 fully interconnected layers). Fully interconnected layers are employed for classification, while convolutional layers aim to obtain features from the input image [76]. VGG19 has a total of 19 layers (16 convolution layers, 3 fully linked layers, five MaxPool layers, and one SoftMax layer). Instead of 7 x 7, three 3 × 3 filters are utilized in the convolution layers, followed by a SoftMax layer at the output [9]. One of the most interesting aspects of the structure is its simplicity. Despite this, it has achieved great accuracy in classification.

3. Res Net

ResNet architecture was created with the goal of improving the efficiency of current CNN architectures like VGGNet, GoogLeNet, and AlexNet. ResNet model types include ResNet_18, ResNet_34, ResNet_50, ResNet_101, and ResNet_152. This architecture won the ImageNet competition (ILSVRC 2015) with a 3.57% error, as well as for the first time, a CNN produced an error rate that exceeded human perception [77]. The previous deep network had the problem of decreasing accuracy and disappearing gradients as network training depth increased. The rise of ResNet tackles this problem by allowing the network to reach an extremely deep level, minimizes the challenge of training deep networks, and enhances performance all at the same time. ResNet built on residual learning. Such kind of learning can help with network training by using the layer inputs as the basis for reference. ResNet-18 contains 18 deep layers, beginning with a convolution layer, then containing 8 residual blocks, then finishing with a fully linked layer. ResNet-50 is like ResNet-18, but it uses a different residual blocks technique it has different number (16) of residual blocks which construct the network. ResNet-50 consists of 50 layers, as does ResNet-101. Thus, it is 101 deep layers with thirty-three residual blocks [72, 78].

4. Mobile Net

Since 2017, the light-weight neural network model is gradually gaining popularity. There are actually two main approaches: creating a lightweight network model and compressing the learned complex network by lowering its accuracy. In the same year, Google proposed a lightweight model: MobileNet. it is a kind of convolutional neural network specifically developed for mobile and embedded vision apps. MobileNet is built on a simplified architecture which utilizes depth wise separable convolutions to develop lightweight deep neural networks with lower latency for mobile and embedded devices.

As of the MobileNetsV1 model, standard convolution has been replaced by depth wise convolution after which follows pointwise convolution, resulting in depth wise separable convolution [79]. The MobileNetV2 design is faster with equivalent accuracy throughout the entire latency range. MobileNet-V2 has 53 layers (52 convolutional with a single fully connected layer). The network's primary part design relies on linear bottlenecks and inverted residuals. The network begins with three convolution layers, then 16 inverted residuals as well as linear bottleneck blocks, then finishes with one convolution layer along with a fully connected layer. The strategy for the network's fundamental part, is the inverted residual block [72]. This model achieves greater accuracy that is around 30-40% faster on a Google Pixel phone compared to MobileNetV1architecture. It perform better than GoogleNet and VGGNet [80].

5. SqueezNet

SqueezeNet model suggested in 2017. SqueezeNet is a type of convolutional neural network having Eighteen layers. The network begins with an independent convolution layer, then has eight fire modules (fire2-9), and finishes with the last convolution layer. The ImageNet database provides a pretrained version of the network, which was trained on over a million pictures. As a result, the network learned comprehensive visual features for a wide range of pictures for classifying images into 1000 various classes. SqueezeNet reaches AlexNet-level accuracy using ImageNet with 50 times less parameters. Furthermore, the authors applied model compression methods in order to reduce SqueezeNet into less than 0.5 MB (510% smaller than AlexNet).SqueezeNet is employed in a variety of applications, including Real-Time Vehicle construct and Model Recognition and indoor obstacle classification [81, 82].

6. **GoogleNet**

GoogLeNet's received the prize the 2014 ILSVRC competition [83]. The network model founded Google's position in both picture classification and object detection. The network has 22 layers, beginning with 3 convolution layers, then adding nine inception blocks, finally finished with a fully linked layer [83]. The primary feature of GoogLeNet is the usage of the perception module. The idea of the module represents a significant milestone in CNN's history. Before getting to its appearance, the standard method simply layered more and more convolution layers in order to build the network deeper and deeper in the hopes of extracting additional features. The fundamental concept of perception is to extract knowledge related to various scales from an image using several convolution kernels then fuse them to create greater representation of the picture, obtaining high-level accuracy and reducing computing cost [78].

7. **Xception**

Xception developed by Google researchers. Google considered inception modules in convolutional neural networks as an intermediary step between standard convolution along with the depth wise separable convolution process (depth wise convolution followed by pointwise convolution). XCeption has an efficient architecture based on two primary features: depth-wise separable convolution plus shortcuts among convolution blocks, just like ResNet. Xception represents a deep convolutional neural network design which employs depth-wise separable convolutions, It is beginning with 2 convolution layers and continues through depthwise separable convolution layers, 4 convolution layers, then a fully linked layer [84].

2.6 multi-criteria decision-making (MCDM)

When it comes to modeling human thinking, two techniques have been receiving a lot of attention in recent decades: fuzzy logic and multi-criteria decision analysis (MCDA), sometimes known as multi-criteria decision-making (MCDM) [34]. decisions Making is one of one of the most complicated aspects of daily life [26]. Whether the decision is great with a lot at risk or a small decision, it must be made. People frequently hesitate to make decisions when they get more difficult and need some form of support [85]. To address that gap, and as knowledge and technology progressed, a field of science known as multi-criteria decision-making (MCDM) is established [27]. Multicriteria decision-making (MCDM) is a multi-use method used in many fields and professional areas involving many criteria or aims, such as healthcare [86], education [87], and military affairs [31].When compared to conventional approaches, MCDM is quickly gaining favor because of its ability to improve decision quality via a more explicit, rational, and effective process [6].

The purpose for employing MCDM methods is based on choosing the most suitable alternatives among a group of alternatives that share the same decision criteria to solve DM issues as a decision matrix, where these alternatives are based on specific criteria [88]. Each MCDM challenge begin and relies on a decision/evaluation matrix, which is a matrix consisting of a set of criteria, a set of alternatives, and the values of the alternatives for each criterion.

$$DM = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$$

where x_{ij} represents the performance measure of the ith alternative on the jth criterion, m represents the number of alternatives, and n represents the number of criteria [89, 90].

Terms associated with MCDM include:

- **Alternatives:** represent the various choices or entities accessible to the decision maker. The set of alternatives is usually considered to be finite, ranging from several states to hundreds. Alternatives provide many techniques for transforming the initial conditions into the desired one. The decision team assesses the needs and goals and proposes alternatives that satisfy the requirements and also meeting as many of the goals as possible [90].
- **Criteria:** represent the various dimensions through which alternatives might be evaluated [91]. Criteria must be able to distinguish between alternatives in a meaningful way (for example, if the color of every alternative is the same or the user is not concerned with the color selection, then color shouldn't be considered a criterion) [92].

The following are the main steps in multicriteria decision making[91, 93] as shown in Figure (2.5):

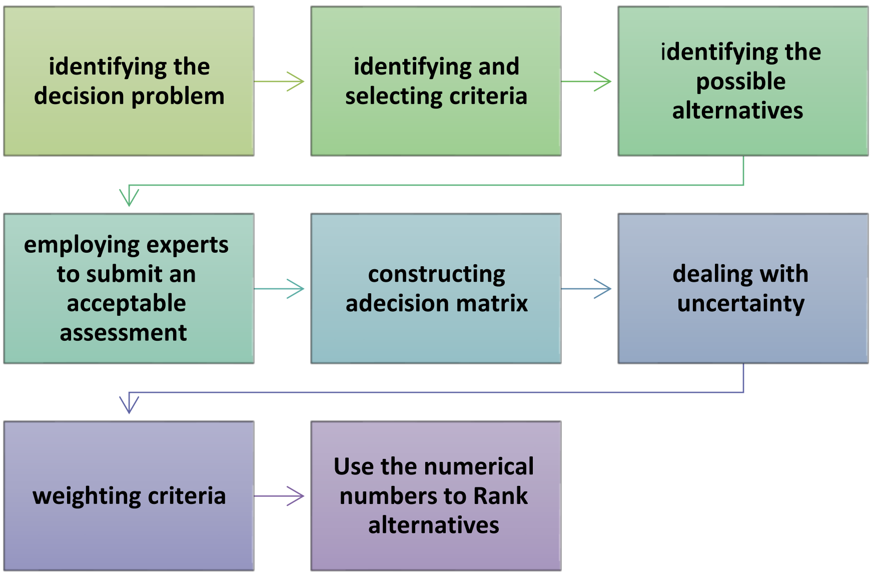


Figure 2.5. MCDM steps

There are two separate approaches used in MCDM, the mathematical (e.g., TOPSIS and VIKOR) used for extract weight for assessment criteria by turning decision-makers' preferences into numerical values and the human approach (e.g., AHP and BWM) to prioritize the alternatives based on the computed weight of the criteria [86, 94]. However, in some situations, these two techniques face a variety of concerns and challenges, such in mathematical technique dealing with (normalization and distance measuring) while human technique, on the other hand, has one major drawback which is the inconsistency ratio caused by pair comparisons[88].

2.7 mathematical approach

The mathematical approach is the usage of formulas, it is used to rank alternatives through a variety of evaluation criteria, the most commonly used MCDM mathematical techniques, each having its own connotation are Simple Additive Weighting (SAW), Hierarchical Adaptive Weighting (HAW), weighted sum model (WSM) and (TOPSIS) Technique for Order of Preference by Similarity to Ideal Solution [86]. The following are the limitations of mathematical techniques: (1) The normalisation procedure is an important component in decision-making research because it standardises numerous evaluation scales by transforming their values into dimensionless figures. Academics have used a variety of data normalisation techniques to reach a clear conclusion, including vector, linear, and linear-max-min normalisation. Different normalisation techniques generate different scales, which alter the behavior of data and eventually influence the final conclusion [95]. (2) In TOPSIS, the way of choosing positive and negative ideal solutions is based on the highest and lowest values, respectively. However, given possible exceptions to its validity, this situation may not be widely applicable. For example, the ideal value for monitoring blood pressure ranges between the maximum and minimum values. (3) The mathematical techniques are incapable of determining the precise weighting of the evaluation factors. As a result, an external mechanism (human techniques) is required to prioritize the evaluation factors [94].

2.7.1 TOPSIS Techniques

TOPSIS was first introduced by Hwang and Yoon for dealing with Multi Criteria Decision Making problems [96]. TOPSIS is one of the most effective ranking techniques that many academics use to identify quickly the optimal or best alternative. This method is one of the most useful for solving real-world situations [97]. It is benchmarking approach based on the premise that the ideal alternative has the greatest level for all attributes, whereas the negative ideal has all of the worst attribute values [98]. TOPSIS assigns ratings to each alternative based on its geometric distance from positive and negative ideal solutions. The best alternative is chosen, which is the one with a short geometric distance to the positive ideal solution and the longest geometric distance to the negative ideal solution [99].

TOPSIS has changed throughout time, combining numerous mathematical concepts and become widely accepted with modifications. The change occurred when traditional TOPSIS is merged with the fuzzy idea proposed by Zadeh in 1965. TOPSIS has the advantage of quickly determining the best alternative. therefore, TOPSIS becomes appropriate for scenarios with a lot of alternatives and attributes. However, TOPSIS's fundamental weakness is its absence of provision for weight elicitation and consistency in checking for judgements [100, 101].

Steps of TOPSIS: as shown in Figure (2.6). TOPSIS algorithm consists six steps [102], which are the following :

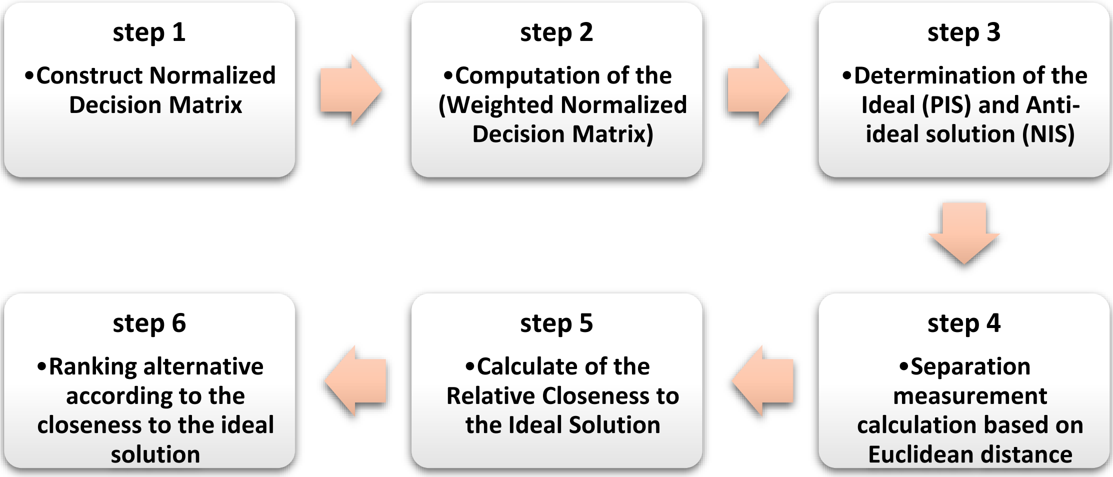


Figure 2.6. TOPSIS steps

Step 1: Normalization of Decision Matrix.

The decision of matrix $X = (xij)\ n{\times}m$ have to be normalized by utilizing the following formula:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{n} x_{kj}^2}}, i = 1, \ldots, n; j = 1, \ldots, m \qquad (2.1)$$

where r_{ij} is the normalized value - rating of the criteria – attribute.

Step 2: Calculation of the Weighted Normalized Decision Matrix. This step involves multiplying the normalization decision matrix by the weight assigned to each criterion.

$$\sum_{j=1}^{n} w_j = 1 \qquad (2.2)$$

where (w_j) is the weight of the (j^{th}) criterion and

$$v_{ij} = w_j r_{ij} \qquad (2.3)$$

are the weighted normalized values.

Step 3: Determination of the ideal and non-ideal solutions

The ideal solution (A*) is:

$$A^* = \{v_1^*, \dots, v_m^*\} = \left\{\left(\max_j v_{ij} \mid j \in \Omega_b\right), \left(\min_j v_{ij} \mid j \in \Omega_c\right)\right\}. \qquad (2.4)$$

non-ideal solution is (A-) is:

$$A^- = \{v_1^-, \dots, v_m^-\} = \left\{\left(\min_j v_{ij} \mid j \in \Omega_b\right), \left(\max_j v_{ij} \mid j \in \Omega_c\right)\right\} \qquad (2.5)$$

The categories of advantage criteria/attributes and cost characteristics are referred to individually as Ωb and Ω_c .

Step 4: Calculate the Separation Measures

This stage involves figuring out the distances between each alternative and the optimal solution.

$$D_i^* = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^*\right)^2} \qquad (2.6)$$

Similarly, distances from non-ideal solutions are calculated as

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \qquad (2.7)$$

Step 5: Compute Relative Closeness to the Ideal Solution

The relative closeness (C_i^*) scales from 0 to 1, with a value closer to 1 suggesting a better alternative. It's calculated as follows:

$$C_i^* = \frac{D_i^-}{D_i^* + D_i^-} \qquad (2.8)$$

Step 6: Rank Order of Preference

The following step will be to rank the alternatives according to their relative closeness values, having the greatest value being the best and placed at the head of the list, and the lowest value at the bottom.

2.7.2 Simple Additive Weighting (SAW)

Simple Additive Weighting (SAW) it is used for ranking process, often known as weighted linear combination or scoring approaches, is a straightforward and widely used multi-attribute decision-making strategy so that through implementing the SAW approach to decision support systems, many decision-making procedures can be easily completed [103]. The weighted average is used in this procedure. An assessment score is produced for every alternative by multiplying the scaled value assigned to that attribute's alternative by the weights of relative importance directly assigned by the decision maker, then summing the results for all criteria. This method has the advantage of being a proportional linear modification of the raw data, which indicates the relative order of magnitude of the standardized scores stays equal [104]. The SAW method's core premises are beneficial in determining the number of weighted performance ratings for each alternative across all attributes. SAW needs a procedure of normalizing the decision matrix (X) to a scale that is able to be compared to all current alternative ratings [105]. There are two attributes in the Simple Additive Weighting Method (SAW): benefit attributes and cost attributes. When making decisions, both attributes have an essential difference in choosing of attributes [106]. The steps of the process for using SAW method to solve problems are shown in Figure (2.7) [107].

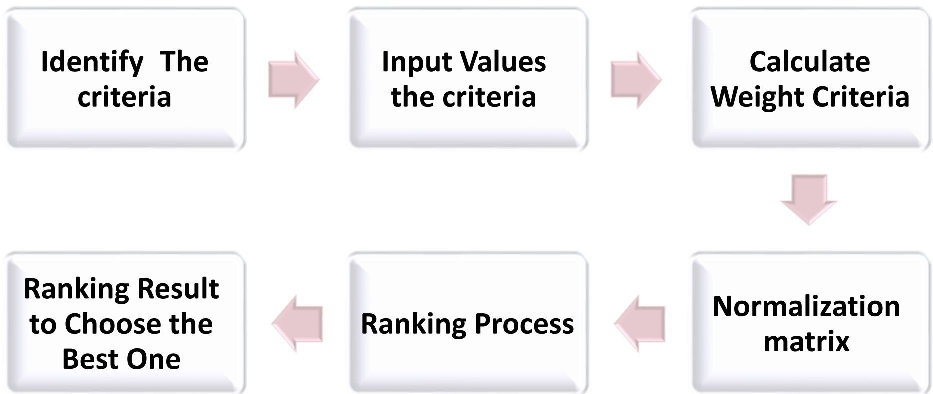


Fig 2.7. Simple Additive Weighting Chart

2.8 Human approaches

The human approach involves humans in the decision-making process. by taking human preferences into account in its calculations [88]. the most commonly used MCDM human-based approaches are Analytic Hierarchy Process (AHP), AHP, Analytic Network Process (ANP), best-worst method

(BWM), and fuzzy-weighted zero-inconsistency (FWZIC). it is utilized to give the evaluation criterion weight [108]. Human techniques have the following limitations: (i) The main issue with human techniques is the possibility of inconsistencies in factor weighting as a result of pairwise comparisons [109]. (ii) Due to the unusual nature of subjective comparisons, the comparison becomes cognitively challenging. To put it another way, comparing two not related factors doesn't seem to be a natural process and hence presents a significant obstacle [110, 111]. (iii) The significant amount of time necessary for pairwise and reference comparisons of numerous factors make this approach more difficult [43].

2.8.1 AHP Technique

The Analytical Hierarchy Process (AHP) is a powerful and adaptable weighted scoring decision making method established at the Wharton School of Business by Saaty that can assist people in setting priorities and making the optimal decision. AHP has been applied in effectively all decision-making applications and is now mostly used in the subject of selection and evaluation, particularly in the domains of engineering, pharmaceuticals, and personal and social fields. In general, implementing AHP relies on the expertise and knowledge of experts or users to identify the elements influencing the decision-making process. AHP assists in the capturing of both subjective and objective assessment measures, giving a valuable tool for assessing the consistency of the evaluation measures and alternatives proposed by the team, and therefore decreasing decision-making bias [112, 113].

There are two phases in using AHP Decision: assessment and hierarchical design. It requires knowledge and familiarity with the subject domain for building the hierarchies. The idea of paired comparisons is vital for the evaluation step. AHP is Eigen values method to pair-wise comparison. It also includes a process for calibrating the numeric scale for measuring both quantitative and qualitative performance [114]. The scale ranges from 1 to 9, with 1 being the least important and 9 being the most important than comprising the whole spectrum of the comparison [115]. When applying AHP to a real-world problem, a decision-maker can change his subjective viewpoint to an objective one, giving the decision-maker the trust that their intuition and experience will not be ignored when determining their final ranking of alternatives [113]. Figure (2.8). shows the stages of the AHP method for solving problems using the methods of AHP[112].

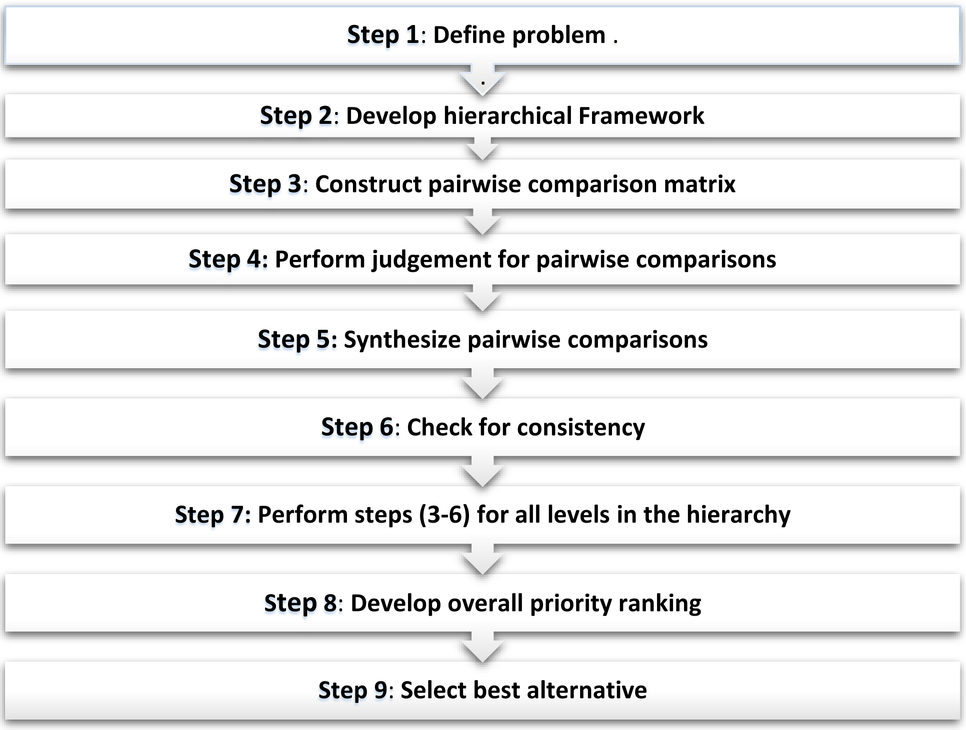


Figure 2.8. Steps of the analytical hierarchy process (AHP)

2.8.2 FWZIC Technique

The fuzzy weighted zero inconsistency (FWZIC) method (published in 2021) was recently introduced for calculating the weight coefficients of criteria with zero consistency. This method computes the importance level in the decision-making process based on differences in expert preference per criterion [98]. since it successfully overcomes the inconsistency problem, which is a prevalent issue that can have significant effects on the accuracy and reliability of the decision-making process, FWZIC is the most ideal subjective weighting method for weighting the relevant criteria. To handle ambiguity, hesitation, and uncertainty in a professional way FWZIC accomplishes zero inconsistency by computing the local and global weight coefficient values of all criteria at a particular hierarchy level separately and precisely [116]. FWZIC capture and reflect decision-makers' accumulated knowledge as well as their subjective opinions. This method is flexible and can be used in a variety of cases. it is beneficial for reducing inconsistency issues caused by the subjective nature of establishing the relative relevance and importance of multiple evaluation criteria utilizing a pairwise comparison approach [86]. In contrast to other methods that need direct comparisons across criteria, FWZIC does not require such comparisons or a large number of mathematical operations, which can be time-consuming, the multiple weighted attributes in FWZIC are independent, therefore adding or removing them require no recalculation. Furthermore, getting feedback from decision-makers (DMs) in FWZIC is straightforward, this means that decision-makers can conserve significant resources, concentrate their attention to other essential parts of the decision-making process and can have more confidence in the final decision because it is based on a precise and consistent weighting of the criteria. The FWZIC method overcomes the shortcomings of the best worst method (BWM) and the analytic hierarchy process (AHP): (i) the procedure's failure to provide decision makers with quick feedback on the consistency of pairwise comparisons, (ii) the lack of accounting for ordinary consistency, and (iii) the absence of a consistency threshold value for evaluating the reliability of results [24]. Figure (2.9) represents the five phases of the FWZIC approach for addressing issues.

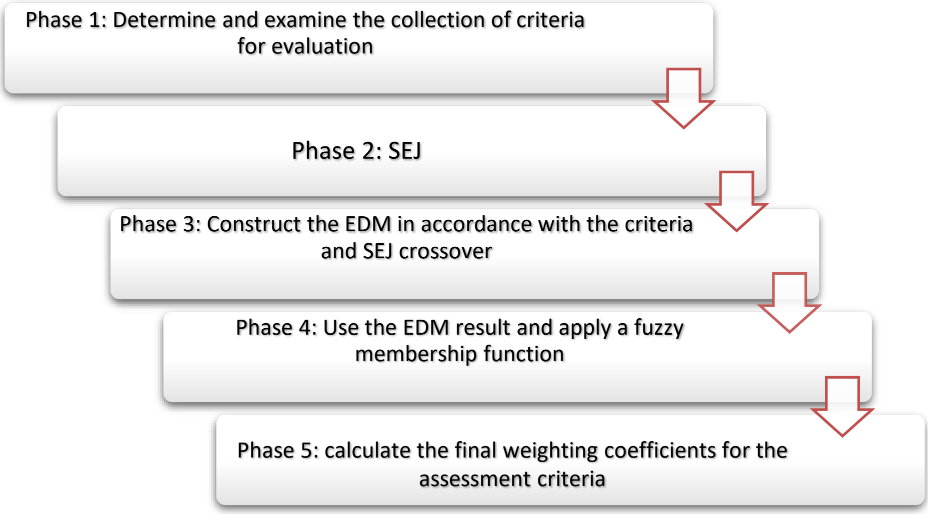


Figure 2.9. Five phases of the FWZIC method.

To determine the weights of the evaluation criteria, the full details of the five phases of FWZIC method are explained in the following subsections [40, 116].

Phase 1: The Definition of Evaluation Criteria Set

This phase has two processes:

Step 1: Investigate and provide the predefined set of evaluation criteria.

Step 2: The behavior and measurement type of each of the obtained criteria, sub-criteria, and relative indicators are used to classify and group them.

Phase 2: Structured Expert Judgment

In this phase, a panel of experts evaluates the defined criteria from the previous step for their importance level. These experts should be specialists with relevant academic and scientific backgrounds. Following that, a nomination procedure is performed in accordance with the following steps:

Step 1: Expert identification: A person who was or is currently active in the case study's subjects and is considered to be knowledgeable by others is referred to be an expert in the FWZIC context. 'Domain' or ‘substantive' experts are another term for specialists who are recognized in the literature.

Step 2: Select an expert: A team of experts is chosen for the case study when expert identification is complete. In this step, at least four specialists are required. To find out their availability and willingness to be considered as possible experts for the panel, all experts from the previous stage are contacted by email.

Step 3: Evaluation form development: The evaluation form is completed since it is a crucial instrument for gathering expert consensus. Before finalization, it is examined by all of the experts from the previous step for reliability and validity.

Step 4: Defining the importance level scale: Using a 1-5 Likert scale, all of the experts chosen in the previous step determine the importance level for each criterion.

Step 5: Converting from linguistic to numerical scale: All preference values are converted from subjective to numerical form for use in the study. Thus, each expert's priority level for each criterion on the utilized Likert scale is translated into a numerical scale.

Phase 3: Expert Decision Matrix (EDM) is constructed based on the crossover of criteria and the Structured Expert Judgement (SEJ)

The EDM is built with the primary parts, which contain criteria and alternatives. The previous phase defines the list of selected experts and each expert's choice within a particular criterion. The EDM is built in this stage. The decision criteria and alternatives are the fundamental components of the EDM.

Phase 4: Fuzzy Membership Function is Applied to the EDM Result

The fuzzy membership function and related defuzzification procedure are applied to the EDM data in this stage, where the data are modified to enhance precision and simplicity of use in subsequent analysis. However, with MCDM, the problem is ambiguous and imprecise due to it is hard to give an exact preference rate to any particular criteria. To solve the issue of imprecise and unclear issues, the fuzzy method uses fuzzy numbers rather than crisp numbers to evaluate the relative value of attributes (criteria). The most popular form of fuzzy number used in fuzzy MCDM is triangular fuzzy numbers (TFNs). TFNs are expressed as A = (a,b,c). Because of their conceptual and computational simplicity, they are widely employed in practical applications.

Definition formula: The membership function (x) of TFN A is given by:

$$\mu A(x) = \begin{cases} \frac{x-a}{b-a} & \text{if } x < a \\ \frac{c-x}{c-b} & \text{if } b \le x \le b \le x \\ 0 & \text{if } x > c \end{cases}, \text{ where } a \le b \le c \qquad (2.9)$$

Remark: Let $\tilde{x} = (a_1, b_1, c_1)$ and $\tilde{y} = (a_2, b_2, c_2)$ be two nonnegative TFNs and $\alpha \in \mathbb{R}_+$. The definition of the arithmetic operations according to the extension principle is as follows:

Addition:

$$\tilde{x} + \tilde{y} = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \qquad (2.10)$$

Subtraction:

$$\tilde{x} - \tilde{y} = (a_1 - c_2, b_1 - b_2, c_1 - a_2) \qquad (2.11)$$

Multiplication:

$$\tilde{x} \times \tilde{y} \cong (a_1 a_2, b_1 b_2, c_1 c_2) \qquad (2.12)$$

Division:

$$\tilde{x}/\tilde{y} \cong (a_1/c_2, b_1/b_2, c_1/a_2) \qquad (2.13)$$

Division on crisp value:

$$\tilde{x}/\alpha = (a_1/\alpha, b_1/\alpha, c_1/\alpha) \qquad (2.14)$$

Defuzzification:

$$\frac{(a + b + c)}{3} \qquad (2.15)$$

Phase 5: Computation of the Final Weight Coefficient Values of the Evaluation Criteria

The final values of the weight coefficients of the evaluation criteria are determined in three sub steps:

1. The fuzzification data ratio is calculated by using (2.10) and (2.13). TFNs used with the previous equations. The process is represented symbolically by (2.16).

$$\frac{\text{Imp } (\widetilde{E1}/C1)}{\sum_{j=1}^{n} \text{Imp } (\tilde{E}1/C_{1j})} \qquad (2.16)$$

2. To determine the final fuzzy values of the weight coefficients of the evaluation criteria, the average values are computed using (2.14). And (2.17) is used to determine the final weight value of each criterion using the Fuzzy EDM.

$$\widetilde{w}_j = \left(\sum_{i=1}^{m} \frac{\mathrm{Imp}(\widetilde{E_{ij}}/C_{ij})}{\sum_{j=1}^{n} \mathrm{Imp}\,(\widetilde{E_{ij}}/C_{ij})}\right)/m\right), \text{ for } i = 1,2,3,\ldots m \text{ and } j = 1,2,3,\ldots n \quad (2.17)$$

3. Defuzzification is used to determine the final weight. Finally, defuzzification methods are used to determine the crisp weight value using (2.15) Prior to computing the final values of the weight coefficients, the weight of importance of each criterion should be allocated based on the total of all criteria's weights for the rescaling purpose used in this step.

2.9 FDOSM

FDOSM is a novel MCDM method that uses the concept of ideal solution and opinion matrix to tackle the highlighted challenges. FDOSM delivers rational decisions because it is based on the DM's (the expert's) opinion. FDOSM can effectively overcome inconsistency, which is a major issue in the human approach, and reduce time consumption when implementing comparisons. FDOSM also reduces the number of mathematical equations. As a result, this method preserves the data while offering a logical decision. Furthermore, in mathematical approach issues, normalisation and the weight are solved. The use of fuzzy numbers can also be used to solve data ambiguity [117].

The steps for FDOSM are as follows:

Step 1: Constructing a decision matrix.

Step 2: Choosing the optimal solution for each criterion (min, max, critical value).

Step 3: Creating an opinion matrix by comparing the ideal solution to other values for each criterion, based on decision-makers' opinions.

Step 4: Transform the opinion matrix to triangular fuzzy numbers.

Step 5: Directing summation using arithmetic means.

Step 6: Making a final decision where the lowest is best one.

The FDOSM technique offered a mathematical model for dealing with MCDM problems using a single decision-making context then followed by a group decision-making context. In the context of decision making, FDOSM is composed of three block units: data input unit, data transformation unit, and data-processing unit. The group decision-making framework is divided into two stages: internal and external aggregations [117].

The FDOSM steps are as follows: The parts that follow describe each unit, as well as the steps and mathematical equations that go with it:

2.9.1 Phase one: Data Input Unit

This approach, like other MCDM approaches, solves MCDM problems involving (m) alternatives (A1, ..., Am) and (n) decision criteria set (C1, ..., Cn). The decision matrix M×N is made up of both of these components (M rows and N columns).

$$D = \begin{array}{c} \\ A_1 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccc} C_1 \; C_2 \; \ldots & & C_n \end{array} \\ \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \end{array} \quad (2.18)$$

This block's output is the decision matrix.

2.9.2 Phase two: Data Transformation Unit

After the creation of the decision matrix, which is the outcome of the first block, FDOSM implements the transformation unit by choosing the ideal solution among the three parameters (minimum, maximum, and critical values). The cost criterion uses a minimum value, where the best solution can be determined by the lowest value and vice versa. The value utilized in different situations, especially when the ideal solution is neither minimal nor maximum, as in the case of blood pressure, is known as critical value philosophy. Here are the steps at this point that are shown and explained:

Step one: Select the ideal solution: Thus, the following is the definition of the ideal solution:

$$A^* = \left\{\left[\left(\max_i v_{ij} \mid j \in J\right), \left(\min_i v_{ij} \mid j \in J\right), \left(Op_{ij} \in I.J\right) \mid i = 1.2.3 \ldots\ldots m\right]\right\} \qquad (2.19)$$

where Op_{ij} is the crucial value when the ideal value is between the max and min, max represents the ideal value with benefit criteria, and min represents the ideal solution with cost criteria.

Step two: Make a reference comparison for each criterion between the ideal solution and other values. There is an implicit technique in place for assigning weights to the evaluation criteria. Subjective measures are used to assess the relative importance of the distinctions between the ideal solution and the alternatives. DMs are asked to determine if their opinions have changed significantly as a result of the relevant differences. Figure (2.10) represents the proposed reference comparisons utilized in the procedure of implicit weight assignment. The DM chooses V31, V22, V43, and V14 as the optimal solution vectors using Eq (2.19). The ideal solution selection step involves comparing the optimal solution to the alternatives.

$$Op_{\text{Lang}} = \left\{\left(\left(\tilde{v}_{ij} \otimes v_{ij} \mid j \in J\right) \cdot \mid i = 1.2.3 \ldots\ldots m\right)\right\} \qquad (2.20)$$

where $\otimes$ denotes a reference comparison between the optimal solution and the alternatives.

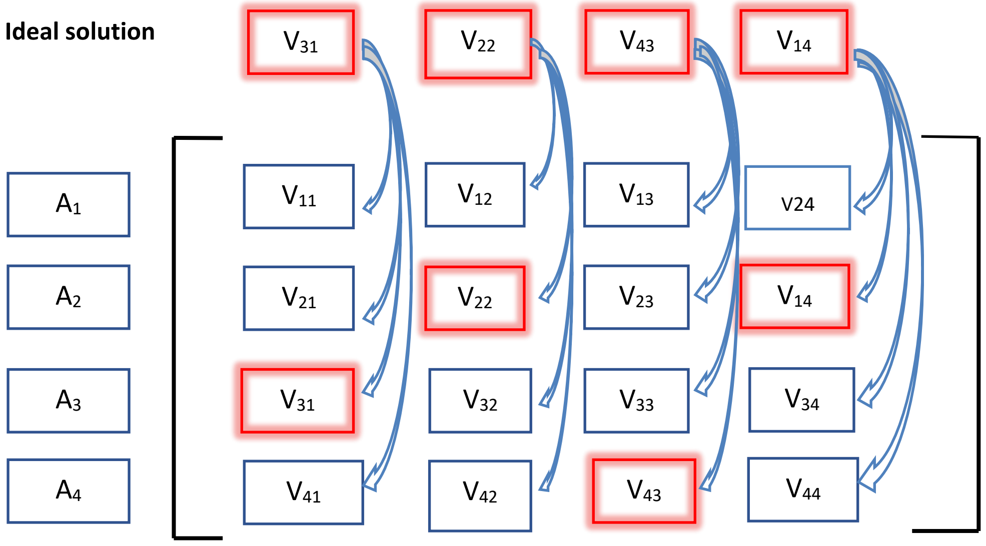


Figure 2.10: Steps of the transformation unit

This stage yields the linguistic term opinion matrix, that is now ready to be turned into fuzzy numbers via fuzzy membership.

$$Op\_\text{Lang} = \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} \begin{bmatrix} op_{11} & \cdots & op_{1n} \\ \vdots & \ddots & \vdots \\ op_{m1} & \cdots & op_{mn} \end{bmatrix} \tag{2.21}$$

2.9.3 Phase three: Data-Processing Unit

This section will be described in the following steps:

Step 1: To generate a fuzzy decision matrix, the opinion terms in the opinion matrix are substituted by triangular fuzzy numbers (TFNs). The fuzzy opinion decision matrix (FDij) is the resulting matrix.

Step 2: By applying an aggregation operator (i.e. arithmetic mean), aggregate the results from the step before it for each alternative. After completing the fuzzy decision matrix, the aggregation procedure is used to select the optimal alternative using one of these aggregation operators:

$$\text{Arithmetic mean } A_{m(x)} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{2.22}$$

$$A_{m(x)} = \frac{\sum (a_f + a_m + a_l)(b_f + b_m + b_l)(c_f + c_m + c_l)}{n} \tag{2.23}$$

Step 3: Using the centroid approach, defuzzification of the aggregation results can be computed as follows:

$$\frac{(a+b+c)}{3} \tag{2.24}$$

2.9.3.1 Individual decision maker

A person's decision-making process based on human knowledge and the usage of mathematical methods, in which eight stages are taken to achieve the final conclusion to address a given problem. The steps are as follows:

define the problem, determine the aim, make a previous decision, generate alternatives, evaluate alternatives, make the proper decision, execute the decision, and follow up to get the ideal solution.

Individual decision maker: He is one individual who uses his knowledge to select the best alternative from a collection of alternatives based on specific criteria. That is, the final decision is made by only one person [117].

2.9.3.2 Group Decision Making

Group MCDM (G-MCDM) indicates to a situation in which more than one DM is required to identify the optimal alternative. G-MCDM approaches collect and merge the knowledge and judgment of experts from various domains. Each expert in a group context offers their own opinion to the criteria needed for subjective assessment. Two common configurations are identified by the academic literature on group decision making: internal and external aggregations [118]. G-MCDM technique is used in this study to aggregate the implicit weights received from each decision maker and produce an overall ranking of alternatives.

2.10 Fuzzy sets

Traditional crisp logic used in computers is binary logic, with either zero or one, true or false, and none in between, which means that no ambiguity. And this with complete certainty, the problem was that the binary did not completely reflect circumstances where the value or model was uncertain or not crisp. This prompted experts to do research in this area [119]. Which has long relied on probability theory and statistics to express uncertainty. Lotfi Zadeh, a scientist, produced the set of fuzzy numbers in 1965. to provide a logical way of dealing with problems such as uncertainty and inaccuracy in real life situation [35].

Fuzzy sets can be defined more precisely as one of the various forms of logic used to express a particular thing that can't be compensated for with an exact value , by applying a function known as a membership function, fuzzy logic sets a numerical value between 0 and 1 to reflect the degree of membership of items in which it is employed to more efficiently and precisely infer uncertain items. so, to identify whether those from a universal set X are members or non-members of a crisp set, a characterizing or discriminating function can be utilized. Using the function, each element in a predetermined crisp set A has been given the value A(x) [120, 121].

$$\mu_A(x) = \begin{cases} 1 & \text{for } x \in A \\ 0 & \text{for } x \notin A \end{cases} \tag{2.25}$$

Hence $\boldsymbol{\mu_A(x)} \in [0, 1]$. The function $\boldsymbol{\mu_A(x)}$takes only the values 1 or 0. whereas the concept of fuzzy set accepts values between [0, 1]. represent the degree of membership.

A fuzzy set R is describing:

$$R = (x, \mu R(x))/x \in A, \mu R(x) \in [0,1] \tag{2.26}$$

Where μR(x) is a membership function; μ R(x) computed the grade at which each element of A belongs to the fuzzy set R. So, to deal with more imprecise and ambiguous information contained in daily life, academics suggest numerous extensions of fuzzy sets, such as:

2.10.1 Trapezoidal Fuzzy Number (TrFN)

Trapezoidal fuzzy number (TFN) is the most commonly used form of fuzzy number. It is a fuzzy number that consists of four points: the lower and upper limits, as well as two break points that set the shape of the trapezoid. the trapezoidal fuzzy number $\tilde{A}$ can be stated as $\tilde{A} = (a_1, a_2, a_3, a_4)$. Figure (2.11). shows how the trapezoidal fuzzy number representation can be interpreted as a membership function [122].

$$\mu_{\tilde{A}}(x) = \begin{cases} 0 & \text{if} \quad x < a_1 \\ x - a_1/\ a_2\ - a_1 & \text{if} \quad a_1 \leq x < a_2 \\ 1 & \text{if} \quad a_2 \leq x < a_3 \\ a_4 - x/a_4 - a_3 & \text{if} \quad a_3 \leq x < a_4 \\ 0 & \text{if} \quad a_4 < x \end{cases} \tag{2.27}$$

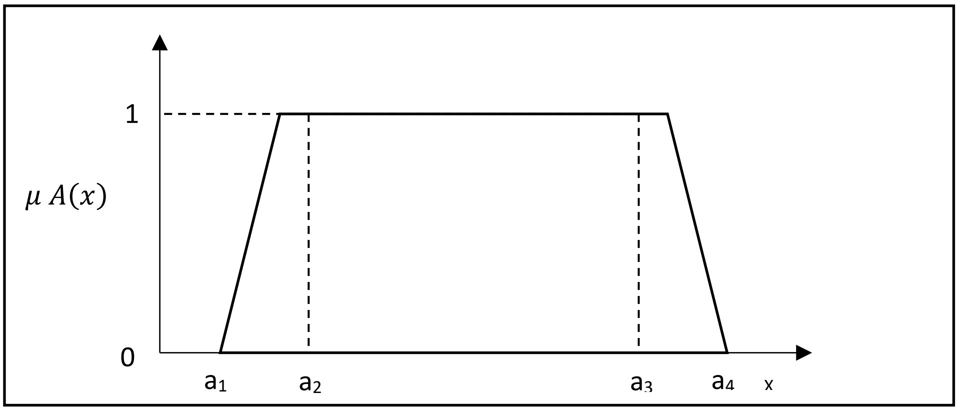


Figure 2.11. Trapezoidal number membership function [122]

The value of each linguistic term together with TrFN can be seen in Table (2.1).

Table 2.1: The value of every linguistic term with TrFN[123]

Linguistic terms	TrFN
Very High (VH)	(0.857, 1, 1, 1)
High (H)	(0.571, 0.714, 0.857, 1)
Medium (M)	(0.286, 0.429, 0.571, 0.714)
Low (L)	(0, 0.143, 0.286, 0.429)
Very Low (VL)	(0, 0, 0, 0.143

The following section [124] shows basic arithmetic operations with TrFN $\widetilde{\boldsymbol{A_1}} = (\boldsymbol{a_1}, \boldsymbol{a_2}, \boldsymbol{a_3}, \boldsymbol{a_4})$ and $\widetilde{\boldsymbol{A_2}} = (\boldsymbol{b_1}, \boldsymbol{b_2}, \boldsymbol{b_3}, \boldsymbol{b_4})$:

1. Addition

$$\widetilde{A_1} \oplus \tilde{A}_2 = (a_1, a_2, a_3, a_{41}) + (b_1, b_2, b_3, b_4) = (a_1 + b_1, a_2 + b_2, a_3 + b_3, a_4 + b_4)$$
(2.28)

2. Multiplication

$$\tilde{A}_1 \otimes \tilde{A}_2 = (a_1, a_2, a_3, a_{41}) \otimes (b_1, b_2, b_3, b_4) = (a_1 \times b_1, a_2 \times b_2, a_3 \times b_3, a_4 \times b_4)$$
(2.29)

3. subtraction

$$\widetilde{A_1} - \tilde{A}_2 = (a_1, a_2, a_3, a_{41}) - (b_1, b_2, b_3, b_4) = (a_1 - b_4, a_2 - b_3, a_3 - b_2, a_4 - b_1)$$
(2.30)

4. division

$$\tilde{A}_1 \div \tilde{A}_2 = (a_1, a_2, a_3, a_{41}) \div (b_1, b_2, b_3, b_4) = (a_1 \div b_4, a_2 \div b_3, a_3 \div b_2, a_4 \div b_1) \quad (2.31)$$

5. Reciprocal values:

$$\tilde{A}_1^{-1}(a_1, a_2, a_3, a_4)^{-1} \left(\frac{1}{a_4}, \frac{1}{a_3}, \frac{1}{a_2}, \frac{1}{a_1}\right) \quad (2.32)$$

2.10.2 Heptagonal fuzzy number

When the nature of the uncertainty is more complex, such as there are cases where ambiguity that occur in real-world issues appears in seven distinct parameters. As a result, it is sometimes impossible to limit the membership function to using a triangular which requires three parameters, or the trapezoidal form, which uses four parameters [125]. For example, the growth rate of a tumor contains seven points and is difficult to describe by a triangular or hexagonal fuzzy number. so, in 2017, A. Mohammed Shapique created the Heptagonal

Fuzzy Number (HFN), which allows for the representation of imperfect knowledge and allows for detailed modeling It also assists us in solving numerous optimization issues and decision-making situations that require seven parameters for many real-life problems. These seven parameters: the lower and upper limits, as well as five intermediate points that form the shape of the heptagon [126].

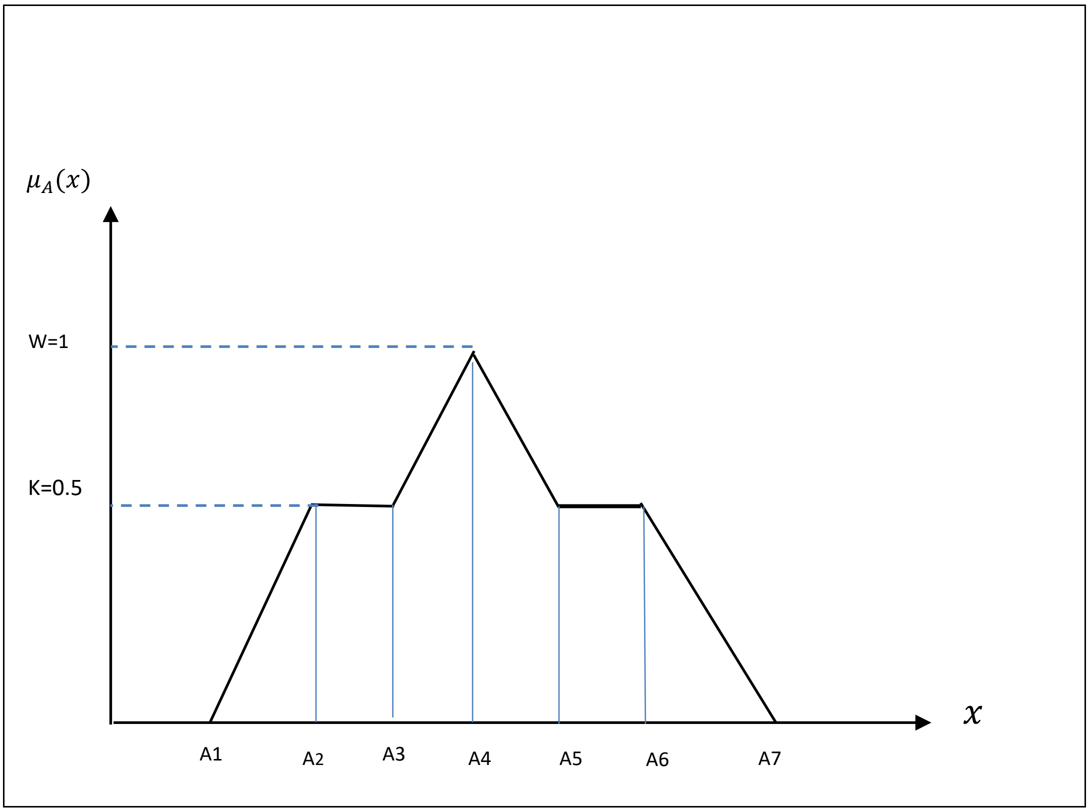


Figure 2.12. Graphical representation of the heptagonal fuzzy number

The HFNs are more flexible and useful in resolving these kinds of problems and can reflect more sophisticated and subtle degrees of uncertainty. The heptagonal fuzzy number offers flexibility to the decision maker to express his or her opinion using two distinct heights, k and w [125, 126]. The LDM (linguistic decision matrix) is transformed into a heptagonal fuzzy number using Table (2.2).

Table 2.2: Heptagonal Linguistic Values and Linguistic terms [127]

Linguistic variable	Heptagonal fuzzy number
Very Low	(0.0,0.0,0.04,0.08,0.12,0.16,0.2)
Low	(0.16,0.2,0.24,0.28,0.32,0.36,0.4)
Medium	(0.36,0.4,0.44,0.48,0.52,0.56,0.6)
High	(0.56,0.6,0.64,0.68,0.72,0.76,0.8)
Very high	(0.8,0.84,0.88,0.92,0.96,1.0,1.0)

The arithmetic operations are defined as follows [128]:

Definition 1. A fuzzy number $\tilde{A}_H(a_1, a_2, a_3, a_4, a_5, a_6, a_7)$ is a heptagonal fuzzy number (H.F.N.), whereas $(a_1, a_2, a_3, a_4, a_5, a_6, a_7) \in \mathbb{R}$ and its membership function are defined as (see Figure 2.12)

$$\mu_{\tilde{A}_H}(x) = \begin{cases} \frac{1}{3}\left(\frac{x - \mathrm{a}_1}{a_2 - \mathrm{a}_1}\right) & \text{for } a_1 \leq x \leq a_2, \\ \frac{1}{3} + \frac{1}{3}\left(\frac{x - a_2}{a_3 - a_2}\right) & \text{for } a_2 \leq x \leq a_3, \\ \frac{2}{3} + \frac{1}{3}\left(\frac{x - a_3}{a_4 - a_3}\right) & \text{for } a_3 \leq x \leq a_4, \\ 1 - \frac{1}{3}\left(\frac{x - a_4}{a_5 - a_4}\right) & \text{for } a_4 \leq x \leq a_5, \\ \frac{2}{3} - \frac{1}{3}\left(\frac{x - a_5}{a_6 - a_5}\right) & \text{for } a_5 \leq x \leq a_6, \\ \frac{1}{3}\left(\frac{a_7 - x}{a_7 - a_6}\right) & \text{for } a_6 \leq x \leq a_7, \\ 0, & \text{for } x < a_1 \text{ and } x > a_7. \end{cases} \tag{2.33}$$

A H.F.N. can be characterized by the so-called interval of confidence at level α as follows:

$$\tilde{A}_{H\alpha}(x) = \{x \in X : \mu_{\tilde{A}_H} \geq \alpha\}$$

$$= \begin{cases} [P^-(\alpha), P^+(\alpha)] & \text{for } \alpha \in \left[0, \frac{1}{3}\right], \\ [Q^-(\alpha), Q^+(\alpha)] & \text{for } \alpha \in \left[\frac{1}{3}, \frac{2}{3}\right], \\ [R^-(\alpha), R^+(\alpha)] & \text{for } \alpha \in \left[\frac{2}{3}, 1\right]. \end{cases} \tag{2.34}$$

Definition 2. If $P^-(\alpha) = \alpha$ and $P^+(u) = \alpha$. Then, the α-cut of $\mu_{\tilde{A}_H}$ is defined as follows:

$$\begin{aligned} [P^-(\alpha), P^+(\alpha)] &= [3\alpha(a_2 - a_1) + a_1, -3\alpha(a_7 - a_6) \\ &\quad + a_7] \text{ for } \alpha \in \left[0, \frac{1}{3}\right], \\ [Q^-(\alpha), Q^+(\alpha)] &= \left[3\left(\alpha - \frac{1}{3}\right)(a_3 - a_2) + a_2, -3\left(\alpha - \frac{2}{3}\right)\right. \\ &\quad \left.\cdot (a_6 - a_5) + a_5\right] \text{ for } \alpha \in \left[\frac{1}{3}, \frac{2}{3}\right], \\ R^-(\alpha), R^+(u) &= \left[3\left(\alpha - \frac{2}{3}\right)(a_4 - a_3) + a_3, -3(\alpha - 1)\right. \\ &\quad \left.\cdot (a_5 - a_4) + a_4\right] \text{ for } \alpha \in \left[\frac{2}{3}, 1\right]. \end{aligned} \tag{2.35}$$

Definition 3. Let $\tilde{A}_H = (a_1, a_2, a_3, a_4, a_5, a_6, a_7)$ and $\tilde{B}_H = (b_1, b_2, b_3, b_4, b_5, b_6, b_7); \forall a_1, a_2, a_3, a_4, a_5, a_6, a_7; b_1, b_2, b_3, b_4, b_5, b_6, b_7 \in \mathbb{R}$, $a_1, a_2, a_3, a_4, a_5, a_6, a_7$; $b_1, b_2, b_3, b_4, b_5, b_6, b_7$ be two HFNs. Then

$$\bar{A}_{H\alpha}(x) \oplus \tilde{B}_{H\alpha}(x)$$

$$= \begin{cases} [3\alpha(a_2 - a_1) + a_1, -3\alpha(a_7 - a_6) + a_7] \text{ for } \alpha \in \left[0, \frac{1}{3}\right], \\ \left[3\left(\alpha - \frac{1}{3}\right)(a_3 - a_2) + a_2, -3\left(\alpha - \frac{2}{3}\right)(a_6 - a_5) + a_5\right] \text{ for } \alpha \in \left[\frac{1}{3}, \frac{2}{3}\right], \\ \left[3\left(\alpha - \frac{2}{3}\right)(a_4 - a_3) + a_3, -3(\alpha - 1)(a_5 - a_4) + a_4\right] \text{ for } \alpha \in \left[\frac{2}{3}, 1\right] \end{cases} \tag{2.36}$$

Definition 4. Let $\tilde{A}_H = (a_1, a_2, a_3, a_4, a_5, a_6, a_7)$ and $\tilde{B}_H = (b_1, b_2, b_3, b_4, b_5, b_6, b_7)$ Then

Addition:

$$\begin{aligned} \tilde{A}_H \oplus \tilde{B}_H &= (a_1, a_2, a_3, a_4, a_5, a_6, a_7) \\ &\quad \oplus (b_1, b_2, b_3, b_4, b_5, b_6, b_7) \\ &= (a_1 + b_1, a_2 + b_2, a_3 + b_3, a_4 \\ &\quad + b_4, a_5 + b_5, a_6 + b_6, a_7 + b_7), \end{aligned} \tag{2.37}$$

Subtraction :

$$\tilde{A}_H \ominus \tilde{B}_H = (a_1, a_2, a_3, a_4, a_5, a_6, a_7) \ominus (b_1, b_2, b_3, b_4, b_5, b_6, b_7) = (a_1 - b_7, a_2 - b_6, a_3 - b_5, a_4 - b_4, a_5 - b_3, a_6 - b_2, a_7 - b_1) \quad (2.38)$$

Scalar multiplication:

$$k\tilde{A}_H = \begin{cases} k(a_1, a_2, a_3, a_4, a_5, a_6, a_7), k \geq 0, \\ k(a_7, a_6, a_5, a_4, a_3, a_2, a_1), k < 0. \end{cases} \quad (2.39)$$

Definition 5. The associated ordinary (crisp) number corresponding to the H.F.N. $\tilde{A}_H = (a_1, a_2, a_3, a_4, a_5, a_6, a_7)$ is defined by

$$\hat{A}_H = \frac{a_1 + a_2 + a_3 + 2a_4 + a_5 + a_6 + a_7}{8}. \quad (2.40)$$

$\hat{A}_H$: Associated ordinary number

2.11 Critical Analysis

Many researchers are trying to offer different solutions to the MCDM problem. Recently, researchers have begun to use FDOSM or extend FDSOM to other fuzzy environments in order to produce better results. In this section, will look at previously published studies that used a new kind of fuzzy environments, the results are as follows:

the authors expanded the FDOSM into the 2-tuple-FDOSM to solve the problem of losing the information during the conversion of a decision matrix into an opinion decision matrix in [28]. This research [129] presents a Fermatean by fuzzy decision opinion score method (F-FDOSM) framework for evaluating Timing side-channel attack countermeasure techniques (TSCA-CTs) in the context of Multiprocessor System-On-Chips (MPSoCs)-based IoT. as well as, a Criteria importance through inter-criteria correlation (CRITIC) technique to weight the criteria. The researcher in [43] extend both FWZIC and FDOSM method by implementing Fermatean probabilistic hesitant-fuzzy sets (named

FPH-FWZIC and FPH-FDOSM) for evaluating agriculture-food 4.0 supply chain approaches. this study [38] extends FDOSM and fuzzy-weighted zero-inconsistency (FWZIC) under neutrosophic fuzzy environment (called NS-FWZIC and NS-FDOSM) for benchmarking smart e-tourism applications. In this work [37], the author extended FDOSM into a fuzzy type-2 environment that utilises interval type-2 trapezoidal (IT2T) membership to Benchmarking of active queue management (AQM) methods of network congestion control. The current research [24] introduces a novel homogeneous Pythagorean fuzzy framework for providing the COVID-19 vaccine dose, by combining a new formulation of the PFWZIC and PFDOSM methods. The researcher in [130] developed the FWZIC and FDOSM techniques for the Q-rung orthopair fuzzy rough sets (q-ROFRS) environment (called q-ROFRS–FWZIC and q-ROFRS FDOSM) for Performance assessment of sustainable transportation in the shipping industry. The proposed work [42], FDOSM and Fuzzy weighted zero-inconsistency FWZIC, have both been extended on the basis of Cubic Pythagorean fuzzy sets CPFS, known as CP-FDOSM and CP-FWZIC for a benchmarking case study of sign language recognition systems. In [36] the author employs in this research the dual hesitant fuzzy environment with both fuzzy weighted zero inconsistency FWZIC and FDOSM approaches to deal with the issue of uncertainty with regard to sustainable transportation: a pavement strategy selection. According to the above critical analysis there is no research that developed FDOSM using the heptagonal fuzzy set.

2.12 Summary

This chapter summarizes the basic concepts and provides general theoretical background on Artificial Intelligent, machine learning and deep learning, also the techniques used with convolutional neural networks (CNN) and closely relates to the thesis methodology. as well as covering the concept of Multi-Criteria Decision Making (MCDM), its approaches (human and mathematical), the new FDOSM technique, fuzzy sets, and some of its types. It also highlights the limitations of each MCDM approaches and the using a new extension of fuzzy number. Finally, critical analysis is described.

Chapter Three: Research Methodology

3.1 Introduction

This chapter discusses the research methodology for this study as described in figure (3.1), including a description of the steps required for extending FDOSM to the Heptagonal fuzzy type. which consists of four phases, each of these four stages satisfies one of the study objectives. The first stage of research: As stated in Section (3.2), (investigation of literature) determines and explains the research gap. The second step (decision matrix definition) explains the process of creating the decision matrix, as described in Section (3.3). The Third step is to applying Heptagonal-FDOSM to a case study, Also, clarifies the two steps of the extension of FDOSM based on the Heptagonal fuzzy type, including data transformation and data processing as presented in Section (3.4). Finally, the fourth step provide validity of the new extension's results using objective validation, outlined in Section (3.5).

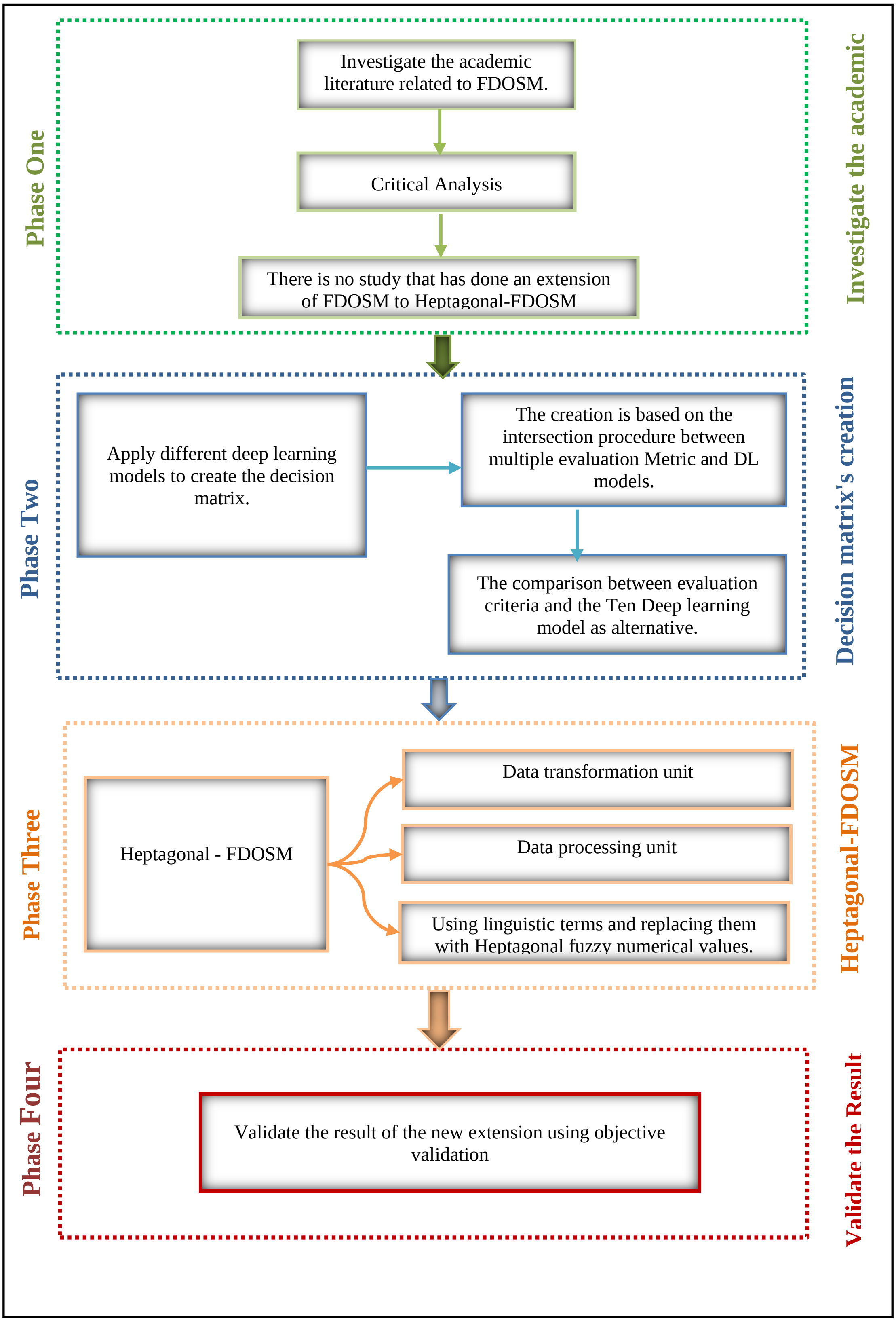


Figure 3.1: Methodology of extend FDOSM to a Heptagonal fuzzy type

3.2 Phase One: Investigating the Literature

In this step, all of academic literature on FDOSM utilizing fuzzy numbers is examined in order to determine the type of fuzzy number employed for extending FDOSM in the academic literature. The results of our investigation showed that no previous study had been conducted on the usage of heptagonal fuzzy numbers in the research and development of FDOSM. The following summary highlights a gap in the academic literature and presents the main contribution of our research, allowing us to identify which deep learning model is the best.

3.3 Phase Two: Decision Matrix's Definition Phase

The primary goal of this stage is to create a DM decision matrix depending on the intersection of several evaluation criteria in performance metrics and models. Important concepts like criteria, alternatives, and decision matrix have to be defined at this stage in every multi-criteria decision making (MCDM) scenario. In our suggested method, the following terms are defined:

3.3.1 Definition of Alternatives

The alternative represents the set of aims or (solutions) available to a particular problem.in this study, the decision matrix consists of 10 CNN powerful architectures which are including: (AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, Xception, and ResNet-101) that to be ranked when employing the new extension of FDOSM from which decision makers must choose.

These ten models were utilized as alternatives, for their capability to classify different medical photographs based on how well they can extract different types of features from images [5, 131]. also, they are more effective in detecting huge amounts of data; developing learning and conducting correlation to provide faster outcomes for classification than existing techniques [132]. Furthermore, it performed well in recognition of images applications, obtaining up-to-date scores on a variety of benchmarks. Their effectiveness comes from their capability to identify spatial patterns and features in images via a hierarchical architecture of layers that conduct convolution processes and extract features at various levels of abstraction [10]. It is able to discovering relevant features with no the need for human interaction [70].

3.3.2 Definition of Evaluation Criteria

Evaluation metrics that have been used are actually critical to getting the optimal classifier. They operate in a common classification of data process in two stages: training and testing. It is used to improve the classification algorithm during the training process. For now, the evaluation metric has been employed to determine the efficiency of the generated classifier [9]. The criteria that are used to evaluate the models are: accuracy, BACC (Balanced Accuracy), precision, recall, Specificity, and F1 score. four estimation parameters were utilized: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). A true positive end result happens when the model correctly predicts the positive class, while a true negative outcome happened when the model rightly identifies the negative class. The false positive outcome comes up when the model incorrectly predicts the positive class, and a false negative outcome takes place when the model wrongly predicts the negative class [133]. Figures (3.2) shows the entire collection of criteria used during this study. the following step, some of the most popular evaluation metrics are mentioned below [133-135]:

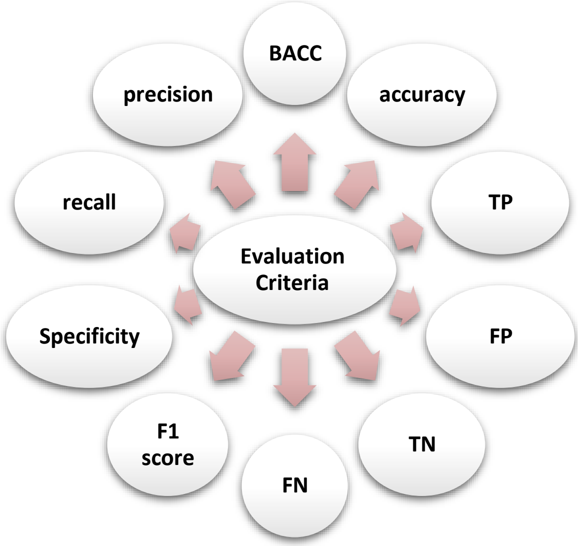


Figure 3.2. Evaluations metrics were employed in this study.

- **Accuracy:** Calculates the ratio of "correct predictions" to the total number of predictions made by the same class.

$$\mathbf{ACC} = \frac{\mathbf{TP+TN}}{\mathbf{TP+FP+FN+TN}} \tag{3.1}$$

- **Recall, True Positive rate (TPR), Sensitivity:** The True Positive Rate (also called Sensitivity) is computed as the number of correct positive predictions (TP) that have been identified divided by the total amount of positive (true positive and false negative).

$$\text{Recall} = \frac{\mathbf{TP}}{\mathbf{TP+FN}} \tag{3.2}$$

- **Precision or Positive predictive value (PPV):** is calculated by dividing the number of "correct positive predictions (TP)" for samples in a given class by the total number of predicted patterns in a positive class (TP + FP) for samples belonging to this class. Precision measures the number of predicted presences is actually true.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3.3}$$

- **F-score**: is the average of recall and precision, yielding a balanced accuracy metric whose values are sensitive to both underestimation and overestimation.

F_score $= \frac{\mathbf{2*TP}}{\mathbf{2*TP+FP+FN}}$ (3.4)

- **Specificity (SPC), Selectivity or True negative rate (TNR):** is computed by dividing the total amount of negatives (N) by the number of true negative predictions (TN). In a small percentage of circumstances, if the outcome is negative, the model will be as well negative, as determined by the formula below.

Specificity $= \frac{\mathrm{TN}}{\mathrm{TN+FP}}$ (3.5)

- **Balanced Accuracy (BACC)**

It is the arithmetic average of sensitivity and specificity Balanced accuracy: A high balanced accuracy score shows model comprehensiveness. The metric combines true negatives and true positives. The inclusion of both the minority and majority classes makes models with high balanced accuracy valuable in situations where completeness is required. It is also used when the test set is either single or unbalanced[136].

$$BC = \frac{\left(\left(\frac{TP}{TP+FN}\right)+\left(\frac{TN}{FP+TN}\right)\right)}{2} \quad (3.6)$$

3.3.3. Construct the Decision Matrix:

In this section, a crossover between alternatives (deep learning models) and performance evaluation criteria is established. So, a combination of 10 deep learning models (AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, Xception, and ResNet-101) and ten evaluation criteria (TP, TN, FP, FN, accuracy, BACC, precision, , Specificity, and F1 score) represents the basic structure of the decision matrix. The very first column of the decision matrix (DM) shows all of the alternatives as well as evaluation criteria listed in the top row. The rows of the decision matrix display the values of the methods' outcomes in regard to the particular evaluation criteria. Table (3.1) illustrates the construction of the decision matrix that have identified.

Table 3.1: decision matrix structure

MODELS	TP	FN	FP	TN	BACC	ACC	Recall,	Precision	F Score	Specificity
AlexNet										
VGG-16										
VGG-19										
SqueezeNet										
GoogleNet										
MobileNet-V2										
ResNet-18										
ResNet-50										
ResNet-101										
Xception										

3.3.4. Data Set Description

In this study, datasets are currently being created. Building models for classification comprises three stages. The initial step in constructing diagnostic models is to collect X-Ray images from trustworthy sources and preprocess the data so that it is ready for use in DL models. Second, the training (learning process) is done by evaluating instances using a training dataset. Third, deep learning methods are applied when combined with other different datasets, often known as dataset testing. Finally, models of diagnosis that produce an adequate result can be regarded as suitable models of diagnosis. Six datasets that are publicly accessible have been utilized as the main source of Chest X-Ray (CXR) images. The dataset employed for this research comprises CXR medical images for healthy and COVID-19-infected participants. This is a public dataset gathered by Dr. Joseph Cohan and is available to researchers via GitHub. The images represent patients with acute respiratory distress syndrome (ARDS), severe acute respiratory syndrome (SARS), and Middle East respiratory syndrome (MARS) [137]. The dataset contains 340 images, including CT scans, frontal and non-frontal chest X-rays (CXR). In addition, the second data set used a publicly accessible medical imaging dataset that included 55 chest X-ray images of COVID-19 patients. The third dataset, acquired from the Kaggle repository [138], has 5,679 two-class CXR images of both healthy and patients with COVID-19 infection. The dataset consists of two categories: 669 images of healthy people and 2,905 images of COVID-19 patients. The fourth COVID-19 medical dataset, similarly from the Kaggle source, includes 348 CXR images, having an equal distribution of 174 images for infected and healthy people. The fifth medical collection includes 280 two-class CXR images of infected and healthy individuals. The final dataset collected from the Roboflow repository comprises 199 images of COVID-19 patients and 1,965 images of healthy persons. Figure (3.3) shows instances of medical imaging from infected and healthy people. This study is focused on the frontal view of X-ray images for both normal and infected individuals, and also included CT scans for the two distinct groups. To address class imbalance problems class labels are distributed equally through the dataset. As a result, the data set used in this study includes 669 images for normal as well as abnormal situations, yielding a total of 1,338 images for the entire data set. Table (3.2) offers more details about the COVID-19 experimental dataset utilized in this study.

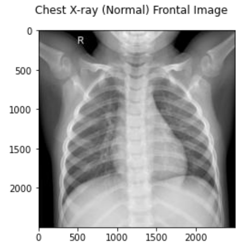
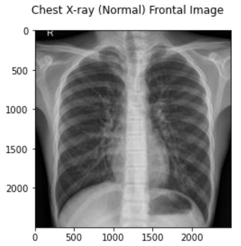
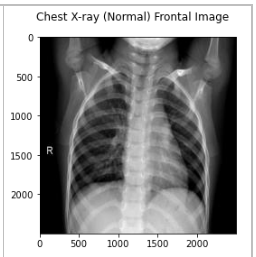
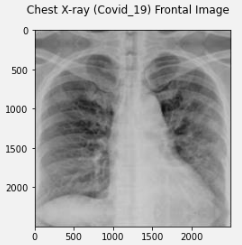
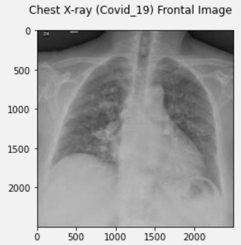
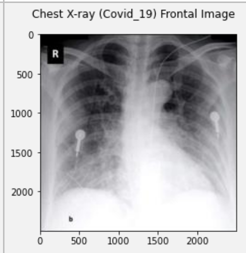
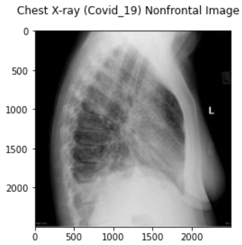
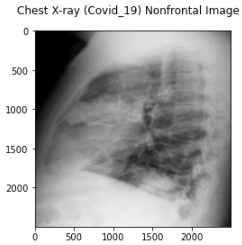
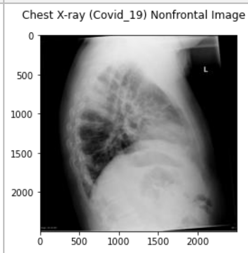
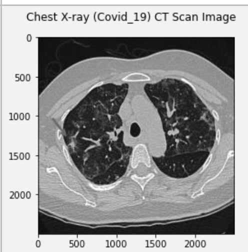
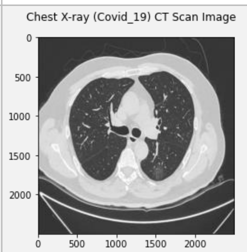
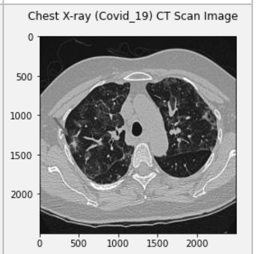
images of Normal Chest			
Frontal Chest images diagnosed with COVID-19			
Nonfrontal Chest images diagnosed with COVID-19			
CT-scan images diagnosed with COVID-19			

Figure 3.3 chest image instances from the specified public dataset, comprising normal CXR, CT-Scan images, and COVID-19 frontal and non-frontal CXR images.

Table 3.2: Description of selected datasets

Dataset	Repo	Samples	#Total	Selected Samples	#Selected	Dataset URL
X-Ray (Dr Joseph Cohan)	GitHub	COVID-19	340	COVID-19	260	“https://github.com/ieee8023/covid-chestxray-dataset”
X-ray Dataset	GitHub	COVID-19	55	COVID-19		“https://github.com/agchung/Figure1-COVID-chestxray-dataset”
X-Ray (Pneumonia)	Kaggle	PNEUMONIA	4273			“https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia”
		NORMAL	1406	NORMAL	669	
X-Ray	Kaggle	COVID-19	174			“https://www.kaggle.com/fusicfenta/chest-xray-for-covid19-detection”
		NORMAL	174		128	
COVID-19 & Normal-poster anterior (PA) X-rays	Kaggle	COVID-19	140	COVID-19		“https://www.kaggle.com/tarandeep97/covid19-normal-posteroanteriorpa-xrays”
		NORMAL	140	NORMAL	90	
COVID-19 and Pneumonia Scans Dataset	Robofow	COVID-19	199	COVID-19	114	“https://public.roboflow.ai/classification/covid-19-and-pneumonia-scans”
		Healthy	1965	NORMAL		
		Viral Pneumonia	3723	Viral Pneumonia		

COVID-19 CXR images sourced from GitHub and Kaggle range in size from 508 × 500 to 4248 × 3480 pixels. In order to prepare the experimental setting, images have been reduced to 150 × 150 pixels. To meet the model's requirements the Keras "preprocess input" function is utilized to preprocess the input images. Applying the standard classification procedure, the function above made it easier to resize the input images. To evaluate the model, the final dataset was broken down into two sets: 75% for training and 25% for testing. Figure (3.4) shows that the distribution of the lung CXR image collection utilized for training and testing.

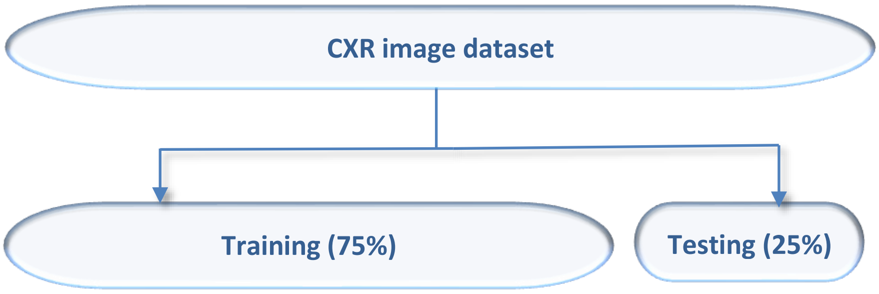


Figure 3.4. the percentage of data taken during the training and testing stages.

To reduce overfitting, a data augmentation procedure is implemented. Augmenting the dataset by generating additional images minimizes the potential risk of overfitting, which can happen due to the model's complexity. Data augmentation boosts the model's generalization capabilities, particularly when using X-ray data sets. Various augmentation strategies have been employed on the training data to increase the model's efficiency. These augmentation procedures attempt to improve the planned model's generalizability. The data augmentations have been performed once to the X-ray training dataset. The augmented X-ray training data has been loaded into a deep learning model to reach the final prediction.

Accurate classification is an essential step in allowing a machine to acquire knowledge from raw data and generate reliable results. Deep transfer learning (DTL) is a deep classification method that makes use of pre-trained CNN models. The DTL method works very effectively with limited training data [139]. DTL is the process of transferring knowledge gained from a source domain that has been extensively trained to a target domain that has less training samples. Using a big dataset from the source domain improves image classification accuracy and reduces training data required. Deep transfer learning

(DTL) is a deep learning technique, particularly convolutional neural networks (CNNs) that includes transferring specific layers of a pre-trained CNN model that has previously been trained with millions of images. According to these researches [10], the CNN model's task-dependent layers those that are not used yet for classification are kept separate apart from the network's design, such as the output classification layer. Models have been trained via the training set. The test dataset is then loaded into ten trained deep diagnostic models to evaluate their capability to detect and distinguish COVID-19 cases from normal ones.

3.4 Phase Three: Heptagonal – FDOSM

At this phase, the system that has been suggested presents the FDOSM stages utilized in the typical evaluation of deep learning methods, as shown in Figure (3.5). The first stage is the data transformation unit from FDOSM, and the second stage is data processing-FDOSM.

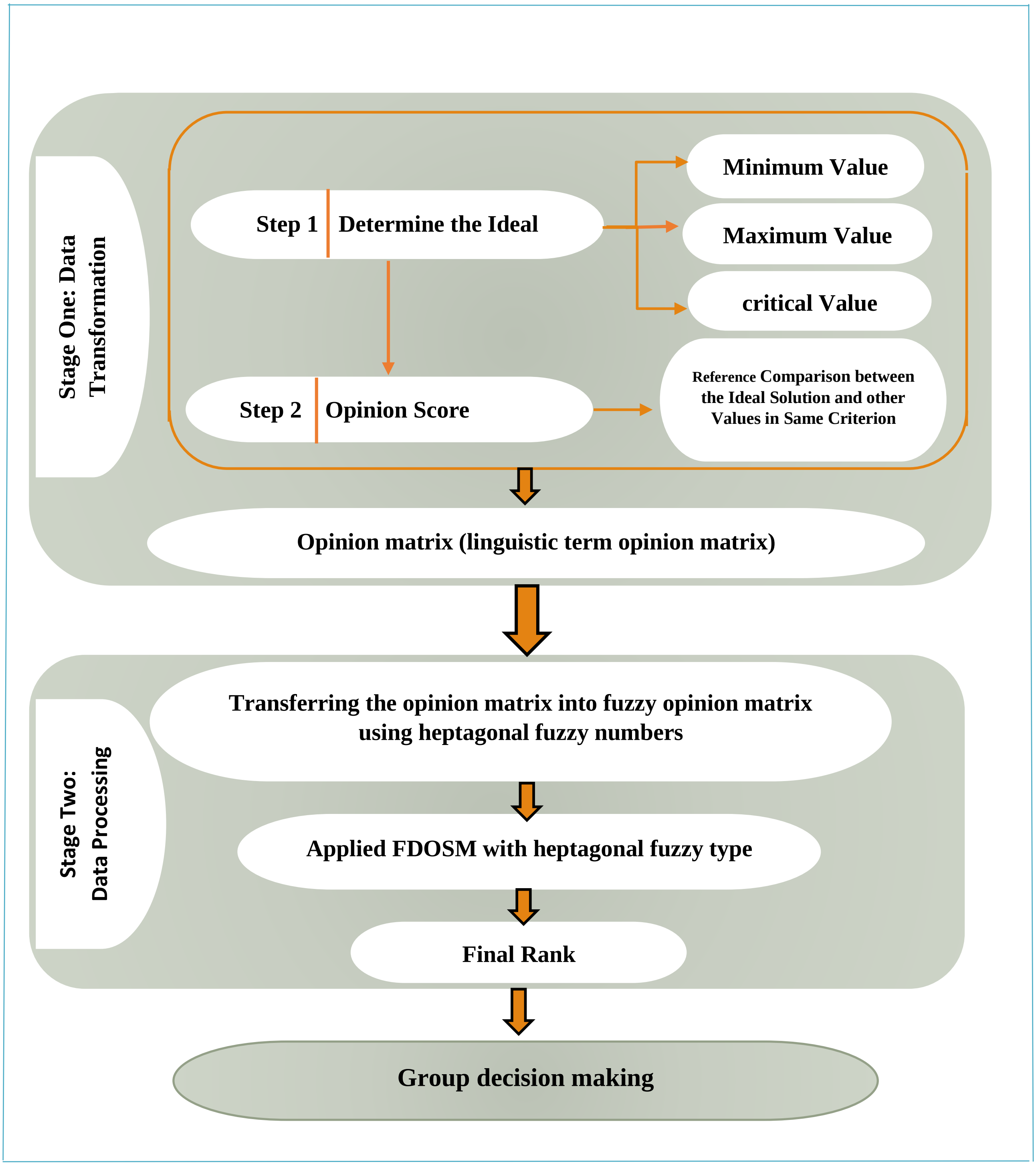


Figure 3.5: Phase of Heptagonal – FDOSM

3.4.1 Data Transformation Unit

This unit transforms the decision matrix to an opinion matrix in two steps:

Step 1: Select the optimal solution for each criterion used in the decision matrix. It can be derived by using the following equation:

$$A^* = \left\{\left[\left(\max_i v_{ij} \mid j \in J\right), \left(\min_i v_{ij} \mid j \in J\right), \left(Op_{ij} \in IJ\right) \mid i = 1,2,3, \dots . m\right]\right\} \quad (3.7)$$

The term MAX refers to the optimal value to the deep learning benefit criteria (TP, TN, accuracy, BACC, precision, recall, Specificity, and F1 score). While the term MIN refers to the optimal solution to the deep learning cost criteria which is (FP, FN). The critical value ($Opij$) occurs when the optimal average value falls somewhere in between the minimum and maximum. The decision maker is in charge of deciding this critical value. It is not essential to identify a critical value in the evaluation criteria used determine deep learning models due to all models in the decision matrix are either cost or benefit criteria

Step 2: once selecting the optimal solution. The second phase involves the expert making a reference comparison between the optimal solution and alternative values in a similar criterion using five linguistic term. The linguistic term scales are categorized as follows: Slight difference (Slight-diff), No difference (No-diff), Huge difference (Huge-diff), Difference (Diff), and Big difference (Big-diff). This step is represented using the following equation:

$$Op_{\text{Lang}} = \left\{\left(\left(\tilde{\tilde{v}} \otimes v_{ij} \mid j \in J\right) \cdot\mid i = 1,2 \dots n\right)\right\} \quad (3.8)$$

The symbol $\otimes$ represents the reference comparison, which compares between both the ideal solution and alternatives. The data transformation unit result is the opinion matrix of the given linguistic terms, as shown below:

$$\text{Op-Lang} = A_1 \begin{bmatrix} op_{11} & \cdots & op_{1n} \\ \vdots & \ddots & \vdots \\ op_{m1} & \cdots & op_{mn} \end{bmatrix} \quad (3.9)$$

Once the opinion matrix has been created, it is translated to fuzzy numbers using a suitable fuzzy membership.

3.4.2 Data Processing Unit:

At this level, two major configurations are used. The first one uses measurement-deep learning models that depend on individual FDOSMs. The second configuration is to measure deep learning models depending on the FDOSM group. The two methodologies are described as follows:

3.4.2.1 Benchmarking DL models using individual Heptagon-FDOSM:

First step: After the creation of the opinion matrix, the fuzzification procedure is implemented out with the goal of transforming opinion matrix into a fuzzy opinion decision matrix. This is accomplished by assigning heptagonal fuzzy numbers to the opinion matrix. This can be achieved by replacing opinion terms with heptagonal fuzzy numbers, which are constructed by the membership function as shown in equation (2.33). We adapted the following table according to the linguistic terms of FDOSM, which are given in Table (3.3).

Table 3.3: Linguistic terms to HFN

Linguistic variable	Heptagonal fuzzy number
No difference	(0.0,0.0,0.04,0.08,0.12,0.16,0.2)
Slight difference	(0.16,0.2,0.24,0.28,0.32,0.36,0.4)
Difference	(0.36,0.4,0.44,0.48,0.52,0.56,0.6)
Big difference	(0.56,0.6,0.64,0.68,0.72,0.76,0.8)
Huge difference	(0.8,0.84,0.88,0.92,0.96,1.0,1.0)

Step 2: Apply the aggregation operation, as shown in equation (2.37), in order to combine the values of the alternatives produced in the previous phase.

Step 3: Apply the centroid defuzzification method to the aggregate result, as shown in equation (2.40). Finally, the lowest value is the best choice.

3.4.2.2 Benchmarking DL methods using collective Heptagon-FDOSM

The primary objective of group decision-making is to combine the decisions of several experts into a single, clear decision. Research conducted by academia finds two common forms of collective decision-making: internal and external aggregations. Internal aggregation attempts to merge the decision matrix of several experts into a single, finalized matrix that can then be used in the decision-making process [117].

External aggregation, on the other hand, includes processing the decision matrix independently to arrive at many decisions, which are then combined to form the final decision. This is demonstrated by equation below:

$$\text{Group } -\boldsymbol{FDOSM} = \oplus \boldsymbol{A}^{*} \tag{3.10}$$

The symbol $\oplus$ indicates the average of a set of numbers (arithmetic mean.), whereas $\oplus A^{*}$ denotes the final result for every specialist. In this research, external aggregations were used.

3.5 Phase Four: objective validation

To demonstrate the final outcome of group decision-making outputs provided by the heptagonal-FDOSM, objective validation is employed in this study. The concept of objective validation is presented by dividing the benchmarking deep learning methods into equal groups.

The number of deep learning methods in each group, as well as the number of groups, had no effect on the objective validation output [44]. To validate the group benchmarking deep learning methods outcomes, the following steps should be taken:

1) The deep learning models are ordered based on Group heptagonal-FDOSM decision making outcomes.
2) dividing the deep learning models into two equal groups
3) Finally, the mean ($\bar{\boldsymbol{x}}$) for each of the groups in GDM results can be calculated according to Eq below.

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (3.11)$$

The comparison process is carried out by using the mean results from each group. The method of comparison relies on the average result in each of the groups. The minimal values of the mean of each group assist to significant results because decisionmakers give the lowest linguistic terms to the ideal solution of each criterion, which is the concept behind FDOSM. As a result, it is assumed that the first group has the minimum mean to test the validity of the outcome, and it therefore is compared to the second group. The mean result for the second group should be larger or equal to the result of the first group. If the evaluation results consistent with the assumptions, then the results are correct.

3.6 Summary

This chapter describes the methodology used in the thesis to achieve the research objectives, as the proposed system extend the FDOSM method by using Heptagonal fuzzy numbers, which consists of four main phases, each of these four stages satisfies one of the study objectives. The first stage of research: investigation of literature by determining and explains the research gap. The second step explains the process of creating the decision matrix which include identifying alternatives (DL models), criteria (evaluation metric). The Third step is to applying Heptagonal-FDOSM to a case study, Also, clarifies the two steps of the extension of FDOSM based on the Heptagonal fuzzy type, include data transformation and data processing unit. Finally, the fourth step provides the validity of the new extension's results using objective validation.

Chapter Four: Result and Discussion

4.1 Introduction

This section presents and discusses the results of a benchmarking method for choosing the optimal DL model using heptagonal-FDOSM methods. in section (4.2) the conclusions reached for developing the suggested method are provided where the decision maker identified the ideal solution and performed reference comparisons between the optimal solution along with other values of alternatives according to the same criteria in order to generate a matrix of the decision maker's opinion within linguistic terms. this section (4.3) presenting fuzzy opinion decision matrix for both the individual and collective context of decision makers. a comparative analysis of the findings was conducted with the outcomes of the basic FDOSM, as described in Section (4.4). Finally, the results of this study have been validated in (4.5).

4.2 opinion matrix result

In this part, the opinion matrix employed for the evaluation and benchmarking deep learning models will be outlined. The above procedure is achieved through the conversion of the original decision matrix shown in Table (4.1) to the opinion matrix based on the personal preferences presented by three decision makers making use of the five Likert scales. According to the concept of FDOSM, the decision maker identifies the ideal solution, which is specified in Equation (3.7). To build the decision-maker's opinion matrix, reference comparisons are performed between the most ideal solution as well as other values of alternatives according to the same criteria, as shown in Equation (3.8). Table (4.2) shows the opinion decision matrix constructed from the choice preferences of the first, second, and third decision makers, respectively.

Table 4.1: Case Study (Decision Matrix)

MODELS	TP	FN	FP	TN	BACC	ACC	Recall	Precision	F Score	Specificity
AlexNet	472	38	147	363	417.5	0.818627	0.92549	0.76252	0.718417	0.711765
VGG-16	411	99	68	442	426.5	0.836275	0.805882	0.858038	0.711073	0.866667
VGG-19	481	29	106	404	442.5	0.867647	0.943137	0.819421	0.780844	0.792157
SqueezeNet	407	103	73	437	422	0.827451	0.798039	0.847917	0.698113	0.856863
GoogleNet	427	83	71	439	433	0.84902	0.837255	0.85743	0.73494	0.860784
MobileNet-V2	496	14	54	456	476	0.933333	0.972549	0.901818	0.879433	0.894118
ResNet-18	480	30	53	457	468.5	0.918627	0.941176	0.900563	0.852575	0.896078
ResNet-50	486	24	1	509	497.5	0.97549	0.952941	0.997947	0.951076	0.998039
ResNet-101	509	1	4	506	507.5	0.995098	0.998039	0.992203	0.990272	0.992157
Xception	503	7	2	508	505.5	0.991176	0.986275	0.99604	0.982422	0.996078

Table 4.2: The opinion matrix of the three decision makers

opinion matrix for expert 1										
MODELS	TP	FN	FP	TN	BACC	ACC	Recall	Precision	F Score	Specificity
AlexNet	DI	DI	H.D	DI	H.D	H.D	S.D	S.D	H.D	B.D
VGG-16	B.D	H.D	B.D	DI	H.D	H.D	DI	DI	H.D	DI
VGG-19	S.D	DI	H.D	DI	DI	H.D	S.D	S.D	H.D	B.D
SqueezeNet	H.D	S.D	B.D	S.D	DI	H.D	B.D	B.D	H.D	DI
GoogleNet	DI	S.D	B.D	S.D	DI	H.D	DI	DI	H.D	DI
MobileNet-V2	S.D	S.D	DI	S.D	S.D	DI	S.D	S.D	B.D	S.D
ResNet-18	S.D	DI	B.D	NO.D	S.D	S.D	S.D	S.D	B.D	S.D
ResNet-50	S.D	S.D	NO.D	NO.D	NO.D	S.D	S.D	S.D	NO.D	NO.D
ResNet-101	NO.D	NO.D	B.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D
Xception	NO.D	S.D	NO.D	NO.D	NO.D	NO.D	S.D	S.D	NO.D	NO.D
opinion matrix for expert 2										
MODELS	TP	FN	FP	TN	BACC	ACC	Recall	Precision	F Score	Specificity
AlexNet	B.D	B.D	H.D	H.D	B.D	H.D	DI	H.D	DI	B.D
VGG-16	B.D	H.D	B.D	DI	DI	B.D	B.D	B.D	DI	DI
VGG-19	S.D	S.D	H.D	B.D	DI	DI	DI	B.D	DI	B.D
SqueezeNet	DI	H.D	B.D	DI	DI	B.D	H.D	B.D	B.D	DI
GoogleNet	DI	H.D	B.D	DI	DI	DI	B.D	B.D	DI	DI
MobileNet-V2	NO.D	DI	DI	DI	S.D	S.D	S.D	DI	S.D	DI
ResNet-18	S.D	B.D	DI	DI	S.D	S.D	DI	DI	S.D	DI
ResNet-50	S.D	B.D	NO.D	NO.D	NO.D	NO.D	DI	NO.D	NO.D	NO.D
ResNet-101	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	S.D
Xception	NO.D	S.D	NO.D	NO.D	NO.D	NO.D	S.D	NO.D	NO.D	S.D
opinion matrix for expert 3										

MODELS	TP	FN	FP	TN	BACC	ACC	Recall	Precision	F Score	Specificity
AlexNet	DI	DI	H.D	H.D	DI	H.D	S.D	H.D	H.D	H.D
VGG-16	B.D	B.D	B.D	B.D	DI	B.D	DI	B.D	H.D	DI
VGG-19	S.D	DI	H.D	B.D	DI	B.D	S.D	B.D	B.D	B.D
SqueezeNet	B.D	B.D	B.D	DI	DI	B.D	B.D	B.D	H.D	DI
GoogleNet	B.D	B.D	B.D	DI	DI	B.D	DI	B.D	B.D	DI
MobileNet-V2	NO.D	DI	DI	DI	S.D	DI	NO.D	DI	DI	S.D
ResNet-18	S.D	DI	DI	DI	S.D	DI	S.D	DI	DI	S.D
ResNet-50	S.D	DI	NO.D	NO.D	NO.D	NO.D	S.D	NO.D	S.D	NO.D
ResNet-101	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D
Xception	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D

*NO. D = No difference, S.D = Slight Difference, DI = Difference, B.D = Big Difference, H.D = Huge Difference

After comparing the expert's ideal solution with the remaining values for the exact same criterion, the three experts' opinions are displayed in the Table above

4.3 fuzzy opinion decision matrix

In the subsequent step, this study demonstrates the fuzzy opinion decision matrix. This procedure involves transforming an opinion matrix into a fuzzy opinion decision matrix through substituting the linguistic terms along with Heptagonal fuzzy numbers based on to the compensation Table (3.3), resulting in a fuzzy opinion decision matrix, which is illustrated in Tables (4.3).

Table 4.3: fuzzy opinion decision matrix (Expert 1)

CRITERIA	AlexNet	VGG-16	VGG-19	SqueezeNet	GoogleNet	MobileNet-V2	ResNet-18	ResNet-50	ResNet-101	Xception
TP	0.36	0.56	0.16	0.8	0.36	0.16	0.16	0.16	0	0
	0.4	0.6	0.2	0.84	0.4	0.2	0.2	0.2	0	0
	0.44	0.64	0.24	0.88	0.44	0.24	0.24	0.24	0.04	0.04
	0.48	0.68	0.28	0.92	0.48	0.28	0.28	0.28	0.08	0.08
	0.52	0.72	0.32	0.96	0.52	0.32	0.32	0.32	0.12	0.12
	0.56	0.76	0.36	1	0.56	0.36	0.36	0.36	0.16	0.16
	0.6	0.8	0.4	1	0.6	0.4	0.4	0.4	0.2	0.2
FN	0.36	0.8	0.36	0.16	0.16	0.16	0.36	0.16	0	0.16
	0.4	0.84	0.4	0.2	0.2	0.2	0.4	0.2	0	0.2
	0.44	0.88	0.44	0.24	0.24	0.24	0.44	0.24	0.04	0.24
	0.48	0.92	0.48	0.28	0.28	0.28	0.48	0.28	0.08	0.28
	0.52	0.96	0.52	0.32	0.32	0.32	0.52	0.32	0.12	0.32
	0.56	1	0.56	0.36	0.36	0.36	0.56	0.36	0.16	0.36
	0.6	1	0.6	0.4	0.4	0.4	0.6	0.4	0.2	0.4
FP	0.8	0.56	0.8	0.56	0.56	0.36	0.56	0	0.56	0
	0.84	0.6	0.84	0.6	0.6	0.4	0.6	0	0.6	0
	0.88	0.64	0.88	0.64	0.64	0.44	0.64	0.04	0.64	0.04
	0.92	0.68	0.92	0.68	0.68	0.48	0.68	0.08	0.68	0.08
	0.96	0.72	0.96	0.72	0.72	0.52	0.72	0.12	0.72	0.12
	1	0.76	1	0.76	0.76	0.56	0.76	0.16	0.76	0.16
	1	0.8	1	0.8	0.8	0.6	0.8	0.2	0.8	0.2
TN	0.36	0.36	0.36	0.16	0.16	0.16	0	0	0	0
	0.4	0.4	0.4	0.2	0.2	0.2	0	0	0	0
	0.44	0.44	0.44	0.24	0.24	0.24	0.04	0.04	0.04	0.04
	0.48	0.48	0.48	0.28	0.28	0.28	0.08	0.08	0.08	0.08
	0.52	0.52	0.52	0.32	0.32	0.32	0.12	0.12	0.12	0.12
	0.56	0.56	0.56	0.36	0.36	0.36	0.16	0.16	0.16	0.16
	0.6	0.6	0.6	0.4	0.4	0.4	0.2	0.2	0.2	0.2
BACC	0.8	0.8	0.36	0.36	0.36	0.16	0.16	0	0	0
	0.84	0.84	0.4	0.4	0.4	0.2	0.2	0	0	0
	0.88	0.88	0.44	0.44	0.44	0.24	0.24	0.04	0.04	0.04
	0.92	0.92	0.48	0.48	0.48	0.28	0.28	0.08	0.08	0.08
	0.96	0.96	0.52	0.52	0.52	0.32	0.32	0.12	0.12	0.12
	1	1	0.56	0.56	0.56	0.36	0.36	0.16	0.16	0.16
	1	1	0.6	0.6	0.6	0.4	0.4	0.2	0.2	0.2

ACC	0.8	0.8	0.8	0.8	0.8	0.36	0.16	0.16	0	0
	0.84	0.84	0.84	0.84	0.84	0.4	0.2	0.2	0	0
	0.88	0.88	0.88	0.88	0.88	0.44	0.24	0.24	0.04	0.04
	0.92	0.92	0.92	0.92	0.92	0.48	0.28	0.28	0.08	0.08
	0.96	0.96	0.96	0.96	0.96	0.52	0.32	0.32	0.12	0.12
	1	1	1	1	1	0.56	0.36	0.36	0.16	0.16
	1	1	1	1	1	0.6	0.4	0.4	0.2	0.2
Recall	0.16	0.36	0.16	0.56	0.36	0.16	0.16	0.16	0	0.16
	0.2	0.4	0.2	0.6	0.4	0.2	0.2	0.2	0	0.2
	0.24	0.44	0.24	0.64	0.44	0.24	0.24	0.24	0.04	0.24
	0.28	0.48	0.28	0.68	0.48	0.28	0.28	0.28	0.08	0.28
	0.32	0.52	0.32	0.72	0.52	0.32	0.32	0.32	0.12	0.32
	0.36	0.56	0.36	0.76	0.56	0.36	0.36	0.36	0.16	0.36
	0.4	0.6	0.4	0.8	0.6	0.4	0.4	0.4	0.2	0.4
Precision	0.16	0.36	0.16	0.56	0.36	0.16	0.16	0.16	0	0.16
	0.2	0.4	0.2	0.6	0.4	0.2	0.2	0.2	0	0.2
	0.24	0.44	0.24	0.64	0.44	0.24	0.24	0.24	0.04	0.24
	0.28	0.48	0.28	0.68	0.48	0.28	0.28	0.28	0.08	0.28
	0.32	0.52	0.32	0.72	0.52	0.32	0.32	0.32	0.12	0.32
	0.36	0.56	0.36	0.76	0.56	0.36	0.36	0.36	0.16	0.36
	0.4	0.6	0.4	0.8	0.6	0.4	0.4	0.4	0.2	0.4
F Score	0.8	0.8	0.8	0.8	0.8	0.56	0.56	0	0	0
	0.84	0.84	0.84	0.84	0.84	0.6	0.6	0	0	0
	0.88	0.88	0.88	0.88	0.88	0.64	0.64	0.04	0.04	0.04
	0.92	0.92	0.92	0.92	0.92	0.68	0.68	0.08	0.08	0.08
	0.96	0.96	0.96	0.96	0.96	0.72	0.72	0.12	0.12	0.12
	1	1	1	1	1	0.76	0.76	0.16	0.16	0.16
	1	1	1	1	1	0.8	0.8	0.2	0.2	0.2
Specificity	0.56	0.36	0.56	0.36	0.36	0.16	0.16	0	0	0
	0.6	0.4	0.6	0.4	0.4	0.2	0.2	0	0	0
	0.64	0.44	0.64	0.44	0.44	0.24	0.24	0.04	0.04	0.04
	0.68	0.48	0.68	0.48	0.48	0.28	0.28	0.08	0.08	0.08
	0.72	0.52	0.72	0.52	0.52	0.32	0.32	0.12	0.12	0.12
	0.76	0.56	0.76	0.56	0.56	0.36	0.36	0.16	0.16	0.16
	0.8	0.6	0.8	0.6	0.6	0.4	0.4	0.2	0.2	0.2

the Table above, offer fuzzy opinion matrices, which are created by changing each decision-maker's opinion matrix into a fuzzy opinion matrix. The other experts' fuzzy opinion matrices are then displayed in Tables A1. and A2. of the Appendix.

After displaying the fuzzy opinion matrices, an aggregation formula (2.37) is applied based on Table (4.3); each alternative was aggregated to obtain the findings, as shown in Table (4.4).

Table 4.4: aggregation step for three Experts

aggregation for Experts 1							
AlexNet	5.16	5.56	5.96	6.36	6.76	7.16	7.4
VGG-16	5.76	6.16	6.56	6.96	7.36	7.76	8
VGG-19	4.52	4.92	5.32	5.72	6.12	6.52	6.8
SqueezeNet	5.12	5.52	5.92	6.32	6.72	7.12	7.4
GoogleNet	4.28	4.68	5.08	5.48	5.88	6.28	6.6
MobileNet-V2	2.4	2.8	3.2	3.6	4	4.4	4.8
ResNet-18	2.44	2.8	3.2	3.6	4	4.4	4.8
ResNet-50	0.8	1	1.4	1.8	2.2	2.6	3
ResNet-101	0.56	0.6	1	1.4	1.8	2.2	2.6
Xception	0.48	0.6	1	1.4	1.8	2.2	2.6
aggregation for Experts 2							
AlexNet	6.16	6.56	6.96	7.36	7.76	8.16	8.4
VGG-16	5.04	5.44	5.84	6.24	6.64	7.04	7.4
VGG-19	4.24	4.64	5.04	5.44	5.84	6.24	6.6
SqueezeNet	5.28	5.68	6.08	6.48	6.88	7.28	7.6
GoogleNet	4.64	5.04	5.44	5.84	6.24	6.64	7
MobileNet-V2	2.44	2.8	3.2	3.6	4	4.4	4.8
ResNet-18	3	3.4	3.8	4.2	4.6	5	5.4
ResNet-50	1.08	1.2	1.6	2	2.4	2.8	3.2
ResNet-101	0.16	0.2	0.6	1	1.4	1.8	2.2
Xception	0.48	0.6	1	1.4	1.8	2.2	2.6
aggregation for Experts 3							
AlexNet	6.04	6.44	6.84	7.24	7.64	8.04	8.2
VGG-16	5.24	5.64	6.04	6.44	6.84	7.24	7.6
VGG-19	4.64	5.04	5.44	5.84	6.24	6.64	7

SqueezeNet	5.24	5.64	6.04	6.44	6.84	7.24	7.6
GoogleNet	4.8	5.2	5.6	6	6.4	6.8	7.2
MobileNet-V2	2.64	3	3.4	3.8	4.2	4.6	5
ResNet-18	2.8	3.2	3.6	4	4.4	4.8	5.2
ResNet-50	0.84	1	1.4	1.8	2.2	2.6	3
ResNet-101	0	0	0.4	0.8	1.2	1.6	2
Xception	0	0	0.4	0.8	1.2	1.6	2

next, the defuzzification equation (2.40) is applied to the previous matrix to obtain the final result for each decision maker.

4.3.1 Individual Decision Making

This section presents the DL models' benchmarking results of the three decision makers utilizing the individual context as presented in Table (4.5).

Table 4.5: The final results of individual decision making

	EXPERT (1)		EXPERT (2)		EXPERT (3)	
	score	Rank	score	Rank	score	Rank
AlexNet	6.337143	9	7.337143	10	7.205714	10
VGG-16	6.937143	10	6.234286	8	6.234286	8
VGG-19	5.702857	7	5.434286	6	5.834286	6
SqueezeNet	6.302857	8	6.468571	9	6.434286	9
GoogleNet	5.468571	6	5.834286	7	6	7
MobileNet-V2	3.6	4	3.605714	4	3.805714	4
ResNet-18	3.605714	5	4.2	5	4	5
ResNet-50	1.828571	3	2.04	3	1.834286	3
ResNet-101	1.451429	2	1.051429	1	0.857143	1
Xception	1.44	1	1.44	2	1.245714	2

According to FDOSM philosophy, the best possible alternative is the one that is closer to the no difference linguistic phrase (the ideal solution) which having the smallest value and vice versa. Table (4.5) show the final outcomes for each expert based on the Opinion Matrix and the Heptagon Fuzzy Opinion

Matrix, Figure (4.1) illustrates the variations between the outcomes based on expert opinions.

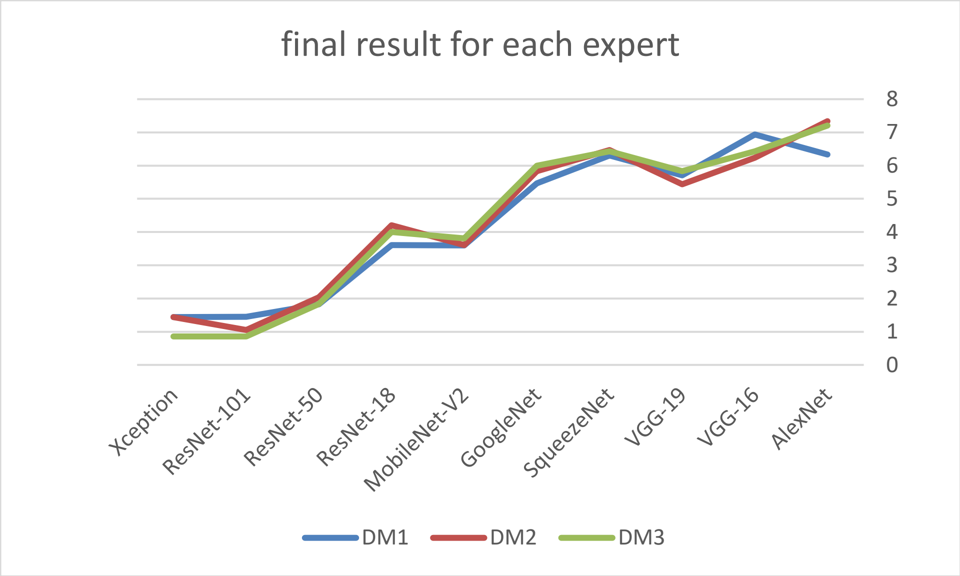


Figure 4.1. The final result for each expert with arithmetic mean

Based on the benchmarking outcome of this scenario, the best alternative for the first decision-maker was "Xception" with a score of "1.44". While (ResNet-101) is the best alternative to the second and third experts, with scores of "1.051429, 0.857143", respectively. this variation is caused by the decision-makers' preferences. On the other hand, the worst possible alternative for the first decision-maker with the farthermost value from the ideal solution is "VGG-16" with a score of "6.937143", while for the second and third decision-makers, the worst alternative is "AlexNet" with scores of "7.337143, 7.205714", respectively.

It is observed that the outcome of the best alternative employing Heptagonal FDOSM produced results that are similar to the expert's opinion, as indicated in the Table (4.2). Furthermore, Table (4.2) shows an alignment in the worst possible alternatives between the preceding table and expert opinion.

4.3.2 Group Decision Making

Group decision making is most significantly frequently used concept in the literature. This section offers the final decision within the structure of group decision making (GDM). Once there is a difference in ranking scores due to the decision-makers' opinions, group decision making is employed. Group decision making has been utilized for ranking alternatives based on all expert opinions. Furthermore, group decision-making is required to address the issue of differences in the final ranking.

To successfully complete the final result of the GDM aggregation process for benchmarking deep learning models in this scenario, the opinions of all three decision makers have to be merged using the "arithmetic mean" into a single the final decision utilizing external group decision making. Table (4.6) displays the GDM's final outcome.

Table 4.6: The final result of the group FDOSM

group decision making		
	score	Rank
AlexNet	6.96	10
VGG-16	6.468571	9
VGG-19	5.657143	6
SqueezeNet	6.401905	8
GoogleNet	5.767619	7
MobileNet-V2	3.670476	4
ResNet-18	3.935238	5
ResNet-50	1.900952	3
ResNet-101	1.12	1
Xception	1.375238	2

According to Table (4.6) the best model is "ResNet-101", that is got the better possible score, with a value of "1.12". On the other side, the model

"AlexNet" had the worst score, with a value of "6.96". The differences in ranking scores are impacted by the perspectives of various decision makers. So, when comparing the GDM conclusion to the decision-makers' opinion matrices, the ranking of deep learning models is similar. The additional flexibility given by this adjustment enables for improved handling of opinion matrix uncertainty whenever comparing the final conclusion of the group decision making context to individual decision maker's opinion matrix.

4.4 Comparative Analysis

The following section offer a comparative analysis between the final rankings derived from the Heptagon-FDOSM with the basic FDOSM in the exact same case study. When comparing basic-FDOSM with Heptagonal-FDOSM, it has been found that the outcome between the Basic-FDOSM and Heptagonal-FDOSM was nearly similar. Table (4.7) shows the variations more clearly for each expert.

Table 4.7: Comparison between Heptagon-FDOSM and basic FDOSM.

MODELS	Expert 1				Expert 2				Expert 3			
	Heptagonal		Basic FDOSM		Heptagonal		Basic FDOSM		Heptagonal		Basic FDOSM	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
AlexNet	6.337143	9	6.4	8	7.337143	10	7.433333	10	7.205714	10	7.15	10
VGG-16	6.937143	10	7.033333	10	6.234286	8	6.533333	8	6.234286	8	5.566667	6
VGG-19	5.702857	7	5.816667	7	5.434286	6	5.7	6	5.834286	6	6.1	7
SqueezeNet	6.302857	8	6.433333	9	6.468571	9	6.7	9	6.434286	9	6.533333	9
GoogleNet	5.468571	6	5.666667	6	5.834286	7	6.133333	7	6	7	6.166667	8
MobileNet-V2	3.6	4	3.85	4	3.605714	4	3.916667	4	3.805714	4	3.966667	4
ResNet-18	3.605714	5	3.883333	5	4.2	5	4.5	5	4	5	4.3	5
ResNet-50	1.828571	3	2.166667	3	2.04	3	2.466667	3	1.834286	3	2.216667	3
ResNet-101	1.451429	2	1.916667	2	1.051429	1	1.5	1	0.857143	1	1.333333	1
Xception	1.44	1	1.833333	1	1.44	2	1.833333	2	1.245714	2	1.666667	2

In the table above, to describe the differences between the Basic-FDOSM and Heptagon-FDOSM, for the first expert, there has been an alteration between the models (AlexNet) and (SqueezeNet), with each model taking the opposite rank from the other alternative. In terms of the second decision maker, the sequence of deep learning models between Heptagon-FDOSM and Basic-FDOSM is identical. There is a variation in the order of deep learning models for the third decision maker, which has resulted in a significant change, including replacing the ranking between (VGG-16, VGG-19, GoogleNet). As a result, the final ranking of Heptagonal-FDOSM is more logical and in line with the opinion of experts. Therefore, the new extension that utilizing 7-parameters are effectively in addressing the issue of uncertainty regarding the evaluation and selecting DL models.

4.5 Objective Validation

Validation is an important aspect in MCDM since it guarantees the accuracy as well as reliability of the process of decision-making. This section discusses the Heptagon-FDOSM outcome validation procedure, which confirms the outcomes derived from DL evaluation and benchmarking group decision-making based on the five points of the Likert scale. In the absence of validation, there will be a riskiness of utilizing an inaccurate model, and this may result in wrong decisions. The objective validation entails combining opinion matrix to create one single opinion matrix and rating the alternatives inside that unified opinion matrix. The benchmarked standard DL models are separated into similar and distinct groups based on the objective validation procedure this process is carried out in various MCDM researches [140].The validation findings are not influenced by either the group number or the total number of DL models (alternatives) inside each group number [141]. To validate the outcomes of deep learning models, multiple procedures must be taken, as shown below

1. The opinion matrix is substituted with a numerical scale then aggregated using the arithmetic mean to get the final score for every alternative.
2. Deep learning models are actually ordered based on the GDM findings.
3. Once sorted, the deep learning models are divided into two groups of equal size.
4. The mean ($\bar{x}$) for each of the groups in the GDM outcome will be calculated as described in equation (3.11).

Table 4.8: Validation of Group Benchmarking Results of deep learning models

Group	Deep Learning models	Mean
1st Group	ResNet-101	1.04
	Xception	
	ResNet-50	
	MobileNet-V2	
	ResNet-18	
2nd Group	VGG-19	4.6
	GoogleNet	
	VGG-16	
	SqueezeNet	
	AlexNet	

The comparison result is based on each group's mean. the mean of each group is used as the basis for comparison. The lowest mean value indicated the most desired (Deep Learning) groups because the DMs have been allocated with the lowest linguistic phrases to the optimal solution of each criteria, which means a better alternative (the optimal solution), that is reflects the concept of FDOSM. whereas, A higher numerical scale reveals a worse alternative. Furthermore, this approach has been developed by researchers and MCDM experts. In that regard, the first group is assumed to represent the lowest mean in order to evaluate the validity of the result, and it is then compared to the second group to assess the validity of the finding.

The second group's mean has to be greater or equal to than the first group. Once the evaluation findings are consistent, then the result can be considered valid. Table (4.8) presents the objective validation results for deep learning models that utilize Heptagonal-FDOSM. The first group had a lower mean (1.04) than the second group that had a higher mean (4.6). The statistical validation results suggest that the heptagonal-FDOSM results for selecting the best DL models presented by the groups are valid and can be ranked systematically.

4.6 Summary

The results of this study are discussed and presented in this chapter. The results for developing the suggested method Heptagonal-FDOSM method to the deep learning models case study were reviewed. The decision matrix includes 10 alternatives and 10 criteria. The results of the Heptagonal-FDOSM are presented in two steps: data transformation to create a matrix of the decision maker's opinion within linguistic terms and data processing to present fuzzy opinion decision matrix for both the individual and group context of decision makers. The final results are compared with the results obtained from the basic FDOSM, finally the result is validated of the new extension using Objective Validation to provide more accurate decision-making results.

Chapter Five: Conclusions and future studies

5.1 Introduction

This chapter is divided into two subsections: 5.2 Conclusions, which at first will provide a full overview of the method that was used as well as the most significant results obtained. Section 5.3 proposed future work using the method outlined in the research paper, as well as any possible future developments.

5.2 Conclusion

This thesis proposed an answer for evaluating and selecting best deep learning models. The evaluation and benchmarking procedure have been carried out utilizing a new development upon one of the multi-criteria decision-making approaches, which refers to the method of decision-making using fuzzy opinion scores.

The methodology for this study, as described in the third chapter, is divided into four sections. The first component (investigate the academic literature related to FDOSM) identifies and discusses the research gap. The second section discusses how to develop a decision matrix to assess and benchmark deep learning models (extract the value of 10 evaluation criteria by applying the 10 deep learning models (alternative) to the data set), from which decision makers must select from these alternatives. The third section of the research methodology discusses how to develop one of the latest decision-making method which is the FDOSM into the Heptagonal-FDOSM to evaluate and select the best deep learning models in order to reduce the uncertainty issue that the FDOSM faced. Finally, the fourth section includes the validity of the new extension's outcomes by using the objective validation.

As for what is discovered from the research, it effectively demonstrated that the development offered in this study is capable of addressing the issue associated with uncertainty while evaluating and selecting the best deep learning models with greater accuracy than the type of fuzzy number employed in the basic method. This is made clear in the comparative analysis, since the outcomes of the new development and the initial method are compared together. an objective validation of the final rank outcomes is performed where the results showed the validity of the conclusions that have been established by utilizing the new development, their results are as following: The first group had a lower mean score (1.04) than the second group (4.6) that had a higher mean score. also, the rankings of the DL models generated by Heptagonal-FDOSM revealed that the best model was "ResNet-101" with score 1.12, while the worst model was "AlexNet" with a score, "6.96". so, the final rank of Heptagonal-FDOSM is more reasonable as well as in line with the opinion of experts.

5.3 Future Works

For future research directions: it is recommended that researchers undertake the following:

1. Developing the FDOSM approach for new fuzzy number, like M-Polar and complicated neutrosophic hesitant fuzzy sets and compare the result with basic FDOSM and Heptagonal-FDOSM.
2. Integrating FDOSM with various additional MCDM methods to improve decision-making by effectively resolving ambiguity and uncertainty.
3. Using different methods to convert fuzzy numbers to crisp numbers, compare them, and identify differences and resulting effects.
4. Using another operator aggregation with Heptagonal-FDOSM and compare the final result with the Heptagonal-FDOSM, to explain the effect of different aggregation operators in the final result.
5. Add additional criteria to the Decision Matrix.

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Appendix:

The fuzzy opinion matrices for each of the last two decision makers are shown in Table A1 and A2.

Table A1: the opinion matrix for the second decision makers

NETWORK	Alex Net	VGG-16	VGG-19	Squeeze Net	Google Net	Mobile Net-V2	ResNet-18	ResNet-50	ResNet-101	Xception
TP	0.56	0.56	0.16	0.36	0.36	0	0.16	0.16	0	0
	0.6	0.6	0.2	0.4	0.4	0	0.2	0.2	0	0
	0.64	0.64	0.24	0.44	0.44	0.04	0.24	0.24	0.04	0.04
	0.68	0.68	0.28	0.48	0.48	0.08	0.28	0.28	0.08	0.08
	0.72	0.72	0.32	0.52	0.52	0.12	0.32	0.32	0.12	0.12
	0.76	0.76	0.36	0.56	0.56	0.16	0.36	0.36	0.16	0.16
	0.8	0.8	0.4	0.6	0.6	0.2	0.4	0.4	0.2	0.2
FN	0.56	0.8	0.16	0.8	0.8	0.36	0.56	0.56	0	0.16
	0.6	0.84	0.2	0.84	0.84	0.4	0.6	0.6	0	0.2
	0.64	0.88	0.24	0.88	0.88	0.44	0.64	0.64	0.04	0.24
	0.68	0.92	0.28	0.92	0.92	0.48	0.68	0.68	0.08	0.28
	0.72	0.96	0.32	0.96	0.96	0.52	0.72	0.72	0.12	0.32
	0.76	1	0.36	1	1	0.56	0.76	0.76	0.16	0.36
	0.8	1	0.4	1	1	0.6	0.8	0.8	0.2	0.4
FP	0.8	0.56	0.8	0.56	0.56	0.36	0.36	0	0	0
	0.84	0.6	0.84	0.6	0.6	0.4	0.4	0	0	0
	0.88	0.64	0.88	0.64	0.64	0.44	0.44	0.04	0.04	0.04
	0.92	0.68	0.92	0.68	0.68	0.48	0.48	0.08	0.08	0.08
	0.96	0.72	0.96	0.72	0.72	0.52	0.52	0.12	0.12	0.12
	1	0.76	1	0.76	0.76	0.56	0.56	0.16	0.16	0.16
	1	0.8	1	0.8	0.8	0.6	0.6	0.2	0.2	0.2
TN	0.8	0.36	0.56	0.36	0.36	0.36	0.36	0	0	0
	0.84	0.4	0.6	0.4	0.4	0.4	0.4	0	0	0
	0.88	0.44	0.64	0.44	0.44	0.44	0.44	0.04	0.04	0.04
	0.92	0.48	0.68	0.48	0.48	0.48	0.48	0.08	0.08	0.08
	0.96	0.52	0.72	0.52	0.52	0.52	0.52	0.12	0.12	0.12
	1	0.56	0.76	0.56	0.56	0.56	0.56	0.16	0.16	0.16
	1	0.6	0.8	0.6	0.6	0.6	0.6	0.2	0.2	0.2
BACC	0.56	0.36	0.36	0.36	0.36	0.16	0.16	0	0	0
	0.6	0.4	0.4	0.4	0.4	0.2	0.2	0	0	0
	0.64	0.44	0.44	0.44	0.44	0.24	0.24	0.04	0.04	0.04
	0.68	0.48	0.48	0.48	0.48	0.28	0.28	0.08	0.08	0.08
	0.72	0.52	0.52	0.52	0.52	0.32	0.32	0.12	0.12	0.12
	0.76	0.56	0.56	0.56	0.56	0.36	0.36	0.16	0.16	0.16
	0.8	0.6	0.6	0.6	0.6	0.4	0.4	0.2	0.2	0.2
ACC	0.8	0.56	0.36	0.56	0.36	0.16	0.16	0	0	0
	0.84	0.6	0.4	0.6	0.4	0.2	0.2	0	0	0
	0.88	0.64	0.44	0.64	0.44	0.24	0.24	0.04	0.04	0.04

	0.92	0.68	0.48	0.68	0.48	0.28	0.28	0.08	0.08	0.08
	0.96	0.72	0.52	0.72	0.52	0.32	0.32	0.12	0.12	0.12
	1	0.76	0.56	0.76	0.56	0.36	0.36	0.16	0.16	0.16
	1	0.8	0.6	0.8	0.6	0.4	0.4	0.2	0.2	0.2
Recall True Positive rate(TPR) Recall ,Sensitivity	0.36	0.56	0.36	0.8	0.56	0.16	0.36	0.36	0	0.16
	0.4	0.6	0.4	0.84	0.6	0.2	0.4	0.4	0	0.2
	0.44	0.64	0.44	0.88	0.64	0.24	0.44	0.44	0.04	0.24
	0.48	0.68	0.48	0.92	0.68	0.28	0.48	0.48	0.08	0.28
	0.52	0.72	0.52	0.96	0.72	0.32	0.52	0.52	0.12	0.32
	0.56	0.76	0.56	1	0.76	0.36	0.56	0.56	0.16	0.36
	0.6	0.8	0.6	1	0.8	0.4	0.6	0.6	0.2	0.4
Positive predective Value (PPV) ,Percision	0.8	0.56	0.56	0.56	0.56	0.36	0.36	0	0	0
	0.84	0.6	0.6	0.6	0.6	0.4	0.4	0	0	0
	0.88	0.64	0.64	0.64	0.64	0.44	0.44	0.04	0.04	0.04
	0.92	0.68	0.68	0.68	0.68	0.48	0.48	0.08	0.08	0.08
	0.96	0.72	0.72	0.72	0.72	0.52	0.52	0.12	0.12	0.12
	1	0.76	0.76	0.76	0.76	0.56	0.56	0.16	0.16	0.16
	1	0.8	0.8	0.8	0.8	0.6	0.6	0.2	0.2	0.2
F Score	0.36	0.36	0.36	0.56	0.36	0.16	0.16	0	0	0
	0.4	0.4	0.4	0.6	0.4	0.2	0.2	0	0	0
	0.44	0.44	0.44	0.64	0.44	0.24	0.24	0.04	0.04	0.04
	0.48	0.48	0.48	0.68	0.48	0.28	0.28	0.08	0.08	0.08
	0.52	0.52	0.52	0.72	0.52	0.32	0.32	0.12	0.12	0.12
	0.56	0.56	0.56	0.76	0.56	0.36	0.36	0.16	0.16	0.16
	0.6	0.6	0.6	0.8	0.6	0.4	0.4	0.2	0.2	0.2
Specificity (SPC), Selectivity, True negative rate (TNR)	0.56	0.36	0.56	0.36	0.36	0.36	0.36	0	0.16	0.16
	0.6	0.4	0.6	0.4	0.4	0.4	0.4	0	0.2	0.2
	0.64	0.44	0.64	0.44	0.44	0.44	0.44	0.04	0.24	0.24
	0.68	0.48	0.68	0.48	0.48	0.48	0.48	0.08	0.28	0.28
	0.72	0.52	0.72	0.52	0.52	0.52	0.52	0.12	0.32	0.32
	0.76	0.56	0.76	0.56	0.56	0.56	0.56	0.16	0.36	0.36
	0.8	0.6	0.8	0.6	0.6	0.6	0.6	0.2	0.4	0.4

Table A2: the fuzzy opinion matrices for the third decision makers

NETWORK	Alex Net	VGG-16	VGG-19	Squeeze Net	Google Net	Mobile Net-V2	ResNet-18	ResNet-50	ResNet-101	Xception
TP	0.36	0.56	0.16	0.56	0.56	0	0.16	0.16	0	0.16
	0.36	0.56	0.16	0.56	0.56	0	0.16	0.16	0	0.16
	0.4	0.6	0.2	0.6	0.6	0	0.2	0.2	0	0.2
	0.44	0.64	0.24	0.64	0.64	0.04	0.24	0.24	0.04	0.24
	0.48	0.68	0.28	0.68	0.68	0.08	0.28	0.28	0.08	0.28
	0.52	0.72	0.32	0.72	0.72	0.12	0.32	0.32	0.12	0.32
	0.56	0.76	0.36	0.76	0.76	0.16	0.36	0.36	0.16	0.36
	0.6	0.8	0.4	0.8	0.8	0.2	0.4	0.4	0.2	0.4
FN	0.36	0.56	0.36	0.56	0.56	0.36	0.36	0.36	0	0.16
	0.4	0.6	0.4	0.6	0.6	0.4	0.4	0.4	0	0.2
	0.44	0.64	0.44	0.64	0.64	0.44	0.44	0.44	0.04	0.24

	0.48	0.68	0.48	0.68	0.68	0.48	0.48	0.48	0.08	0.28
	0.52	0.72	0.52	0.72	0.72	0.52	0.52	0.52	0.12	0.32
	0.56	0.76	0.56	0.76	0.76	0.56	0.56	0.56	0.16	0.36
	0.6	0.8	0.6	0.8	0.8	0.6	0.6	0.6	0.2	0.4
FP	0.8	0.56	0.8	0.56	0.56	0.36	0.36	0	0	0
	0.84	0.6	0.84	0.6	0.6	0.4	0.4	0	0	0
	0.88	0.64	0.88	0.64	0.64	0.44	0.44	0.04	0.04	0.04
	0.92	0.68	0.92	0.68	0.68	0.48	0.48	0.08	0.08	0.08
	0.96	0.72	0.96	0.72	0.72	0.52	0.52	0.12	0.12	0.12
	1	0.76	1	0.76	0.76	0.56	0.56	0.16	0.16	0.16
	1	0.8	1	0.8	0.8	0.6	0.6	0.2	0.2	0.2
TN	0.8	0.36	0.56	0.36	0.36	0.36	0.36	0	0	0
	0.84	0.4	0.6	0.4	0.4	0.4	0.4	0	0	0
	0.88	0.44	0.64	0.44	0.44	0.44	0.44	0.04	0.04	0.04
	0.92	0.48	0.68	0.48	0.48	0.48	0.48	0.08	0.08	0.08
	0.96	0.52	0.72	0.52	0.52	0.52	0.52	0.12	0.12	0.12
	1	0.56	0.76	0.56	0.56	0.56	0.56	0.16	0.16	0.16
	1	0.6	0.8	0.6	0.6	0.6	0.6	0.2	0.2	0.2
BACC	0.36	0.36	0.36	0.36	0.36	0.16	0.16	0	0	0
	0.4	0.4	0.4	0.4	0.4	0.2	0.2	0	0	0
	0.44	0.44	0.44	0.44	0.44	0.24	0.24	0.04	0.04	0.04
	0.48	0.48	0.48	0.48	0.48	0.28	0.28	0.08	0.08	0.08
	0.52	0.52	0.52	0.52	0.52	0.32	0.32	0.12	0.12	0.12
	0.56	0.56	0.56	0.56	0.56	0.36	0.36	0.16	0.16	0.16
	0.6	0.6	0.6	0.6	0.6	0.4	0.4	0.2	0.2	0.2
ACC	0.8	0.56	0.56	0.56	0.56	0.36	0.36	0	0	0
	0.84	0.6	0.6	0.6	0.6	0.4	0.4	0	0	0
	0.88	0.64	0.64	0.64	0.64	0.44	0.44	0.04	0.04	0.04
	0.92	0.68	0.68	0.68	0.68	0.48	0.48	0.08	0.08	0.08
	0.96	0.72	0.72	0.72	0.72	0.52	0.52	0.12	0.12	0.12
	1	0.76	0.76	0.76	0.76	0.56	0.56	0.16	0.16	0.16
	1	0.8	0.8	0.8	0.8	0.6	0.6	0.2	0.2	0.2
Recall True Positive rate(TPR) Recall ,Sensitivity	0.16	0.36	0.16	0.56	0.36	0.16	0.16	0.16	0	0
	0.2	0.4	0.2	0.6	0.4	0.2	0.2	0.2	0	0
	0.24	0.44	0.24	0.64	0.44	0.24	0.24	0.24	0.04	0.04
	0.28	0.48	0.28	0.68	0.48	0.28	0.28	0.28	0.08	0.08
	0.32	0.52	0.32	0.72	0.52	0.32	0.32	0.32	0.12	0.12
	0.36	0.56	0.36	0.76	0.56	0.36	0.36	0.36	0.16	0.16
	0.4	0.6	0.4	0.8	0.6	0.4	0.4	0.4	0.2	0.2
Positive predective Value (PPV) ,Percision	0.8	0.56	0.56	0.56	0.56	0.36	0.36	0	0	0
	0.84	0.6	0.6	0.6	0.6	0.4	0.4	0	0	0
	0.88	0.64	0.64	0.64	0.64	0.44	0.44	0.04	0.04	0.04
	0.92	0.68	0.68	0.68	0.68	0.48	0.48	0.08	0.08	0.08
	0.96	0.72	0.72	0.72	0.72	0.52	0.52	0.12	0.12	0.12
	1	0.76	0.76	0.76	0.76	0.56	0.56	0.16	0.16	0.16
	1	0.8	0.8	0.8	0.8	0.6	0.6	0.2	0.2	0.2
F Score	0.8	0.8	0.56	0.8	0.56	0.36	0.36	0.16	0	0
	0.84	0.84	0.6	0.84	0.6	0.4	0.4	0.2	0	0
	0.88	0.88	0.64	0.88	0.64	0.44	0.44	0.24	0.04	0.04

	0.92	0.92	0.68	0.92	0.68	0.48	0.48	0.28	0.08	0.08
	0.96	0.96	0.72	0.96	0.72	0.52	0.52	0.32	0.12	0.12
	1	1	0.76	1	0.76	0.56	0.56	0.36	0.16	0.16
	1	1	0.8	1	0.8	0.6	0.6	0.4	0.2	0.2
Specificity (SPC), Selectivity, True negative rate (TNR)	0.8	0.36	0.56	0.36	0.36	0.16	0.16	0	0	0
	0.84	0.4	0.6	0.4	0.4	0.2	0.2	0	0	0
	0.88	0.44	0.64	0.44	0.44	0.24	0.24	0.04	0.04	0.04
	0.92	0.48	0.68	0.48	0.48	0.28	0.28	0.08	0.08	0.08
	0.96	0.52	0.72	0.52	0.52	0.32	0.32	0.12	0.12	0.12
	1	0.56	0.76	0.56	0.56	0.36	0.36	0.16	0.16	0.16
	1	0.6	0.8	0.6	0.6	0.4	0.4	0.2	0.2	0.2

الخلاصة

في الســـنوات الأخيرة، حقق التعلم العميق تقدمًا كبيرًا في مجالات مختلفة مثل الرعاية الصـــحية والتعليم والاقتصاد لأنه يمكن أن ينتج نتائج عالية الأداء من خلال قدرته على تفسير البيانات بدقة بما في ذلك تصنيف الصـــور واكتشـــاف الكائنات وغير ذلك الكثير. يعتمد نجاح تطبيقات التعلم العميق بشـــكل كبير على اختيار النموذج الأكثر ملاءمة، حيث يؤثر هذا الاختيار على دقة وكفاءة وموثوقية النتائج. ومع ذلك، أصـــبح اختيار أفضـــل نموذج للتعلم العميق معقدًا بشـــكل متزايد بســـبب الطبيعة المتنوعة للبيانات ومقاييس التقييم المتعددة. لمعالجة هذا التحدي، ظهرت طرق اتخاذ القرار متعدد المعايير (MCDM) كأدوات أساسية لاختيار النموذج الأكثر ملاءمة لمهام محددة. لذلك، تمكنت أحدث طريقة، وهي طريقة القرار الضـــبابي حســـب درجة الرأي (FDOSM)، من حل بعض المشكلات الموجودة بكفاءة والتي لم تتمكن الطرق الأخرى من حلها. ومع ذلك، لا تزال هناك العديد من المشـــكلات في FDOSM وامتداداتها، مثل عدم اليقين. في هذه الدراســـة، تم عمل امتداد ل FDOSM إلى Heptagonal -FDOSM لحل هذه المشكلة. يسمح هذا الامتداد ويوفر تمثيلًا أكثر دقة لآراء الخبراء ومقاييس الأداء. ونتيجة لذلك، تنقســـم منهجية دراســـتنا إلى مرحلتين: الأولى هي إنشـــاء مصفوفة قرار تتضمن مزيجًا من 10 معايير تقييم بالإضافة إلى عشرة نماذج DL. المرحلة الثانية هي توسيع FDOSM إلى بيئة Heptagonal لمعالجة مشـــكلات عدم اليقين التي تواجه FDOSM. كشـــفت نتائج الدراســـة عما يلي: بالنسـبة لصـــانع القرار الفردي، كان أفضـــل بديل للخبير الأول هو "Xception" بدرجة "1.44". بينما (ResNet-101) هو أفضل بديل للخبير الثاني والثالث، بدرجة "1.051429، 0.857143"، على التوالي، من ناحية أخرى، فإن أفضـــل نموذج DL يعتمد على اتخاذ القرار الجماعي هو "ResNet-101" وهو الأفضـل بين جميع النماذج المسـتخدمة، بدرجة "1.12" هذه المرتبة النهائية أكثر منطقية وأقرب إلى رأي صانعي القرار. أخيرًا، تم إجراء التحقق الموضوعي والتحليل المقارن.

جمهورية العراق
وزارة التعليم العالي والبحث العلمي
جامعة تكريت
كلية علوم الحاسوب والرياضيات
قسم علوم الحاسوب

تقييم واختيار أفضل نموذج للتعلم العميق بناءً على التطوير الجديد لـFDOSM

رسالة ماجستير مقدمة الى
مجلس كلية علوم الحاسوب والرياضيات في جامعة تكريت
وهي جزء من متطلبات نيل شهادة الماجستير
في علوم الحاسوب

من قبل الطالبة
رشا عبدالله يوسف

بإشراف
أ.م.د. محمود ماهر صالح

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