International Journal of Electrical and Computer Engineering (IJECE)
Vol. 13, No. 3, June 2023, pp. 3041~3055
ISSN: 2088-8708, DOI: 10.11591/ijece.v13i3.pp3041-3055

Toward enhancement of deep learning techniques using fuzzy logic: a survey

Dhafar Fakhry Hasan[1], AbdulSattar Mohammed Khidhir[2]
[1]Computer Unit, College Medicine, Mosul University, Mosul, Iraq
[2]Department of Computer Systems Technologies Mosul, Technical Institute, Northern Technical University, Mosul, Iraq

Article Info

Article history:

Received Mar 26, 2022
Revised Jun 17, 2022
Accepted Jun 21, 2022

Keywords:

Artificial intelligence
Deep learning
Fuzzy systems
Intelligent systems
Machine learning

ABSTRACT

Deep learning has emerged recently as a type of artificial intelligence (AI) and machine learning (ML), it usually imitates the human way in gaining a particular knowledge type. Deep learning is considered an essential data science element, which comprises predictive modeling and statistics. Deep learning makes the processes of collecting, interpreting, and analyzing big data easier and faster. Deep neural networks are kind of ML models, where the non-linear processing units are layered for the purpose of extracting particular features from the inputs. Actually, the training process of similar networks is very expensive and it also depends on the used optimization method, hence optimal results may not be provided. The techniques of deep learning are also vulnerable to data noise. For these reasons, fuzzy systems are used to improve the performance of deep learning algorithms, especially in combination with neural networks. Fuzzy systems are used to improve the representation accuracy of deep learning models. This survey paper reviews some of the deep learning based fuzzy logic models and techniques that were presented and proposed in the previous studies, where fuzzy logic is used to improve deep learning performance. The approaches are divided into two categories based on how both of the samples are combined. Furthermore, the models' practicality in the actual world is revealed.

Corresponding Author:

Dhafar Fakhry Hasan
Computer Unit, College Medicine, Mosul University
Mosul, Iraq
Email: dhf@uomosul.edu.iq

1. INTRODUCTION

Over the last decade, artificial intelligence (AI) has emerged as one of the most effective applications for advancing humanity in a variety of ways, ranging from medical and disease diagnosis advances to autonomous cars, semantic segmentation, and personal assistants [1]. There has been a demand for many years to build algorithms/computer machines that can do jobs like automated detection [2]. Machine learning (ML), neural networks (NN), computer science intelligence, evolutionary computing, and other cutting-edge technologies have all been included in AI [1], [2]. The focus here is on the highly related and widespread AI sector of deep learning. Deep learning (DL) has recently gained a lot of consideration due to its potential to produce desirable results in a variety of applications [3], [4]. In recent years, DL has made significant progress in computer vision applications, and he has benefited from an increase in attention paid to his theories, which have become extremely generalizable for a wide range of issues [2], [4]. Expert systems (ES), artificial neural networks (ANN), fuzzy logic (FL), and hybrid techniques such as neuro-fuzzy systems, genetic programming neural networks, and others are all examples of AI methodologies.

Deep learning's introduction has considerably aided artificial intelligence's rapid progress [5]. The aim of the design of machine learning in AI is to learn the inner rules and the representation level of the sample data. This helps in using the rules that were learned in creating a universal model that is able to predict unknown data. This makes machines capable of learning like humans and able to recognize or understand data such as texts, images, and sounds. In reality, a standard machine learning algorithm can only learn a limited number of functions due to the limited number of learning parameters [3]. It may not be able to create a suitably complicated function in some circumstances, limiting its generalizing ability of a complex category [5]. For that reason, deep learning appears to mitigate those challenges.

In our daily lives, we might face situations in which we are unable to recognize whether a situation is true or not. The term "fuzzy" is used to describe things that are confusing or ambiguous. In AI, fuzzy logic gives you a lot of flexibility when it comes to reasoning. FL is a type of logic which is very similar to human reasoning. This strategy can be compared to the way of human decision-making [4].

Adaptive neuro-fuzzy inference system (ANFIS) is considered a contemporary composite AI method that integrates the benefits of neural networks with fuzzy logic in a network. This paradigm enables the generation of IF-THEN rules and the functions of the membership from provided data and even the capacity to learn and implement new values on its own [2]. The ANFIS model preserves the fuzzy system's clarity as well as the learning capability acquired through neural networks [3]. For issue resolution, ANFIS employs a combination of backpropagation and regression techniques with different kinds of learning algorithms.

In fact, deep learning concept, that is also common as "image-based machine learning" is considered a very effective process to be used in medical imaging field. A great deal of futuristic height was attained by deep learning techniques to be used for skin lesion analysis in recent times. Deep learning nowadays is considered a continuous task in the computer vision domain that attained significant great results in the segmentation and classification of dermoscopic images through different models that were proposed by different researchers all over the world. Deep convolutional neural networks (DCNNs) is considered one of the most common deep learning models that have attained a noticeable far improved performance [4].

This survey paper aims to review many deep learning models based on fuzzy logic models and techniques that were applied in previous studies, where fuzzy logic was used to improve the deep learning performance. The importance of this study and the gap that this paper fills are that it demonstrates what the researchers studied and applied to several deep learning based on fuzzy logic models under one survey paper. The reminder of this paper is organized as: sections 2 and 3 show details in deep learning, fuzzy logic, and their application. Section 4 discuss neuro fuzzy system. Additionally, section 5 describes the related work. Finally, sections 6 and 7 presents the discussion and some conclusions.

2. DEEP LEARNING AND THEIR APPLICATION

Deep learning is considered as a sort of AI that mirrors the human brain's actions in preparing information and creating indicators for use in decision-making. It is also known as deep neural learning (DNL) or deep neural network (DNN) [4]. Deep learning sets establishes the essential boundaries around the information and aids the computer to learn on its own by perceiving designs through several layers of processing, rather than structuring information to go through predefined conditions. Deep learning networks are able in learning the unsupervised from the unstructured or unlabeled data. Deep learning, in plain terms, is a form of algorithm that looks to be very good at anticipating events [3], [4]. Deep learning involves both data training and learning from previous experiences. It is a promising technique that allows computers to learn new things. This machine learning model relies on the neural network of the humans. This artificial neural network reduces time by preventing people from doing repetitive tasks, and it also reduces the possibility of human error, giving it an overall boost in value [5].

Deep learning (DL), in the format of a multilayer neural network (often known as a DNN), may build deep enough functions to suit functions. Deep learning is a complicated nonlinear backsliding framework as a machine learning technique [6]. With the creation of the neural model (also known as the McCulloch-Pitts model (MP)), the transformation of the biological neuron into such an artificial neuron showed the antecedents of bionic learning in AI [7]. The perception proposal, also termed as a monolayer neural network [8] is the next step. Perceptron can only perform simple linear classification tasks and cannot tackle simple sorting problems such as XOR [7], [8]. The back-propagation technique to overcome the problem of the extensive computations required by two-tier neural networks, which is once again fueling the neural network research boom in the industry [9]. When the deep belief network (DBN) developed in 2006, the notion of deep learning was born, and it quickly rose to the top of many research tests. Deep learning research has exploded in popularity since then [10]. Many deep learning models appears convolutional neural network (CNN), Boltzmann machines (DBM), recurrent neural network (RNN), residual shrinkage (DRSN), attention-based long short-term memory (ABLSTM), and DRSN and spatial-spectral representation (DSSRL) [1], [2], [5]. Even while imprecision, ambiguity, and imprecision are all too often in the actual world, these classic deep learning methods appear to be based on sharp values [7].

The advantage of the DL: the architecture of deep learning is adaptable to new problems in the future. It can create new features from the limited training data sets available. The disadvantage of DL: training is quite expensive due to sophisticated data models. It is difficult for less skilled people to adopt because there is no core theory to tell you how to choose the right deep learning tools [8].

Deep learning is based on the principle of repeated instruction. It teaches the computer how to recognize a pattern and also how to recognize a picture or speech. The computer can then automatically catch that word or voice after it has been recognized [9]. This kind of learning is quite similar to how we people learn. We learned to speak as children by listening to what was going on around us. This is how we learned, and now deep learning is teaching computers using this formula [10].

DL importance: deep learning is critical since it makes our tasks more accurate and efficient. Deep learning is particularly strong when dealing with undeveloped data because of its ability to process enormous quantities of information. As a result, computer vision is a great illustration of a task that deep learning has transformed into something useful for business. Face recognition on Facebook is now possible thanks to deep learning [8].

Deep learning is a subset of a learning machine that has gained popularity in the AI industry. It teaches computers how to learn through examples in order to execute a task that might humans find simple. A deep neural network, or deep neural learning, is another name for it [7].

Neural networks play an important part in deep learning. These are considered as a set of algorithms that we use to detect meaningful associations in datasets, and they mimic the process of the human's brain. Neural networks represent the functioning of the brains of the humans and allow computer algorithms to spot patterns. It also addresses difficult challenges in the fields of data science, AI and machine learning. Artificial neural networks are used in deep learning in order to recognize the hidden patterns of data in a dataset. These algorithms are used to a data set after being trained for enough time [9].

Artificial neural networks are used in deep learning to identify the hidden patterns. These patterns are considered as the links between different variables in a dataset. ANN algorithms are trained on a large amount of data before being applied onto a fresh dataset. Similar to the biological nervous system, these algorithms stimulate the way information is processed and communicated. Deep learning is now deep-seated in our daily lives, from search engines to self-driving cars [6].

2.1. Self-driving cars

Self-driving automobiles, for example, are developed utilizing deep neural networks at a high level, with these autos and employing machine learning techniques. They detect items in the immediate vicinity of the vehicle, the distance between the vehicle and other vehicles, the location of the footway, traffic signals, and the driver's condition, among other things. Tesla, for example, is the most dependable brand when it comes to bringing automated, self-driving cars to market [5].

2.2. Sentiment analysis

Sentiment analysis is considered as the process of using natural language processing, text analysis, and statistics in order to understand and analyze the client's sentiments. A corporation strives to understand its customers' thoughts by listening to what they say and how they say it in order to figure out how they feel about the company. They can also categorize the statements as either good, negative, or neutral [8]. Customers' sentiments can also be found in the form of comments, tweets, reviews, and other forms of social media. These feelings are gathered in an organized or unstructured style by a firm from numerous sources such as Twitter, Facebook, and other social media platforms. Structured data is data that has been arranged and is simple to analyze [10].

Unstructured data refers to datasets that are not owned by a corporation or individual. They are just data that has been gathered from other or unaffiliated sources. For example, independent sources collected data on coronavirus disease (COVID-19) patients. Deep learning can be described as being great for sentiment categorization, sentiment analysis, emotional analysis, opinion/assessment mining, and a variety of other tasks [7].

2.3. Virtual assistant

Virtual personal assistants are often used. They only do or behave in accordance with your instructions. Personal assistants, for example, are extremely useful in chatbots, commuting applications, online training websites, online training instructors, and so on. Make recognizable speech, convert speech to text, and vice versa to deal with natural language processing (NLP) are their major uses. Siri, Amazon Alexa, Google Home, and others are examples [6].

2.4. Social media

To improve its offering, Twitter uses deep learning algorithms. They utilize a deep neural network to access and evaluate a huge amount of data in order to learn over time about the potentials of user preferences. Instagram employs deep learning in preventing the cyber bullying and it deletes the comments that are obnoxious. Furthermore, deep learning is used by Facebook to propose sites, friends, goods, and other items. Furthermore, Facebook's facial recognition system is based on the ANN algorithm, which makes flawless tagging possible [8].

2.5. Healthcare

In healthcare, deep learning is really the fastest-growing topic. Deep learning is often used in smart sensors and devices which use patient records to provide actual data on medical conditions including general health, blood glucose levels, pulse rate, beat counts, and other measures. Medical institutions can use this data to assess the health of specific patients. Also, based on the history of the patient's medical data, identify trends and predict the recurrence of any condition in the future. This technology also aids in medical professionals in analyzing data and in recognizing trends, resulting in faster medical diagnosis and better patient-care. In addition, deep learning is used in medical and pharmaceutical industries and for a variety of objectives, including easy diagnosis and picture segmentation. The CNN, for example, may be used to analyze pictures such as magnetic resonance imaging (MRI) findings, X-rays, and so on [7], [10].

3. FUZZY LOGIC AND ITS APPLICATION

Fuzzy logic is a technique of computing that focuses on "degrees of truth" instead of the traditional "true as 1 or false as 0" Boolean reasoning that the contemporary computer is built on [1]. Human language, like most other aspects of life and the world, is difficult to convert into real numbers such as 0 and 1. Perhaps everything can be described in binary terms in the end is a philosophical topic worth exploring, but most of the data we'd like to give a computer is somewhere in between, as are the outcomes of computing [11]. It might be helpful to think of fuzzy logic as the true way in which thinking works, and binary, or Boolean, logic considered as a particular case. Three important fuzzy strategies utilized in fuzzy system research are the fuzzy set (also known as the type 1 fuzzy set), the type 2 fuzzy set, and the linguistic variable [12].

Fuzzy logic is used to simulate human thinking and cognition in AI systems. Instead of strictly binary situations of truth, fuzzy logic contains 0 and 1 as extreme cases of truth, along with many degrees of truth in between. FL is used in monitoring and controlling machine outcomes based on numerous inputs/input parameters, such as control systems; and designing for judgments without unambiguous probabilities and ambiguities, or with imperfect data, such as NLP capabilities [13].

Furthermore, fuzzy recognition outperforms exact recognition in image segmentation at low frequencies [11]. As a result, traditional deep learning methods focused in precise mathematics can drastically reduce the similarity of the points, affecting the model's learning ability, the pattern recognition result and ultimately lowering the model's prediction accuracy [12]. Fusion is a fantastic technique for combining data from several sources [11], [12]. Different isolated attributes, judgments, sensor outputs, and other sources, as well as various combinations thereof, can be used as these sources. Fusion methods typically helps in improving the system of performance by merging information in a favorable platform that allows for more discriminatory transmission system in certain way [12]. This may be done by creating more reliable functions that can be used across several domains. Fusion can also be used in combining several decision makers, also including classifiers, to actually improve classification accuracy result [13]. Fusion is considered as a power and a wealth technique. If it is used correctly, it may lead to considerable algorithm enhancements [14]. Fuzzy processes are usually associated with fuzzy methods, such as fusion. Fuzzy logic is well-suited to dealing with facts with different levels of belief [13], [14]. This may be done by creating more reliable algorithms that can be used across several domains. Fusion may be used to combine several decision-making, such as predictors, to improve overall classification performance results [12], [14].

For at least two reasons, fuzzy systems have previously shown some usefulness in the deep learning context [15]. To begin, define confusion in common deep learning system applications [14]. In instance, rather than being clearly characterized by 0 or 1, the classes of the characteristics that exist in the real physical world are classed by their level of scope. Another argument is because the fuzzy state is ubiquitous, and accurate mathematics, statistical theory, and stochastic theory are unable to properly address fuzzy issues in practice [14], [16]. Computer vision [17] is considered as one of the most important applications of deep learning. As demonstrated by many experimental tests [14], [18], the updated fuzzy spatial separation classification algorithm performs significantly better and is closer to reality than conventional deep learning models. The last point is that it employs a linguistic variable to illustrate a real language's imprecision and ambiguity. Natural language processing has been found to benefit from deep learning approaches [19].

Language processing includes natural language learning, understanding, and creation NLP. However, fusion models that integrate deep learning and fuzzy systems do not only cope with ambiguity, misunderstanding, and uncertainty in NLP, but they also offer users with intelligible and natural outcomes utilizing language variables [20]. FL is used in a variety of applications; the remainder of this section explains how to utilize it.

3.1. Automobile manufacturing

Automobile manufacturers employ fuzzy logic algorithms in their vehicles to avoid collisions. The braking mechanism is controlled by fuzzy logic, which considers inputs like as weight, speed, and acceleration. This technology is also used by car makers to control fuel injection. This is accomplished using input variables such as maximum load, engine revolutions per minute (RPM), and heat [18].

3.2. Sector of aviation

This approach is used by aircraft to keep a constant height. If the aircraft is not inside the intended height, IF-THEN conditions are used to guarantee that it takes remedial action. Whether the target cruising level is 40,000 feet high, for example, the fuzzy logic will allow the aircraft to restore to that level if it travels lower than the top it [17].

3.3. Applications in the home

Many household appliances, such as air conditioning units, TVs, vacuums, and refrigerator, employ fuzzy logic. It is also utilized to manage water input, cleaning, spin speed, and the time taken washing in washers [10]. The size of the garments, the type of dust, and the level of dirt are all input variables (degree). The washer will accept a big volume of water from the faucet if the garments are large and oily. Because of the huge size of the garments and the nature of the grime, the machine will take quite a long time to clean them [21]. As a result, fuzzy systems have an impact on the deep learning algorithm, thus, this article aims to provide a full understanding of how deep and fuzzy learning systems work together.

4. DEEP NEURO FUZZY SYSTEM

Because deep neuro-fuzzy systems (DNFSs) are a hybrid of ANFIS and DNN classifiers, this part will cover the architecture and concepts of these classifiers, as well as the deep neuro-fuzzy classifier. As the majority of actual classification issues involve nonlinear behavior, ANFIS have been frequently utilized to improve classification outcomes in a variety of nonlinear situations [17]. Rather than using binary logic, which can only be true or false (0 or 1), Zheng *et al*. [19] claims that FL provides a promising approach to real-world problems by utilizing Boolean logic, which is a concept of values which can be partly correct and incompletely false using a membership value between 0 and 1. ANFIS employs the logic of fuzzy and the idea of fuzzy IF-THEN principles to better characterize the ambiguity of human thought. While ANN benefits from its learning experience because to its similarity to the human brain in terms of information processing. As a result, the ANFIS model may include human knowledge as well as self-learning abilities to simulate any scenario [14].

The ANFIS model is made up of five layers as shown in Figure 1. Directed connections connect the nodes of one layer to the nodes of another layer. As a result, each node executes a specific function on its receiving signals to create the output for a single node. As a result, it is commonly referred to as a multilayer feed-forward network. The fundamental goal of the ANFIS is to use a learning method to find the best values for the analogous fuzzy inference system parameters [13].

The ANFIS learning method uses two-pass composite learning algorithms combining gradient descent (GD) and least square modelling approach to update learnable parameters such as membership function and appropriate numbers to achieve lowest error (LSE) [21]. LSE tweaks subsequent parameters throughout the forward run, while GD changes the values of the parameters even during backward pass, this helps in improving the performance of the models [16]. The ANFIS learning method uses two-pass algorithms for composite learning combining GD and least square modeling approach to update learnable strictures such as the function of membership and appropriate numbers to achieve the LSE. LSE tweaks subsequent parameters throughout the forward run, while GD changes values of the parameters even during backward pass to improve the performance of the models using DNN [10].

A single value input, one output, and several hidden layers make up a DNN. It allows maximum features to be collected from low-level characteristics to construct a representation [15], and it allow multiple degrees of intellection to modify the size, number, and structure of each layer. In practice, a single layer has various nodes, each of which is connected by a present set of weights from previous levels. The choosing of weights is an important step that takes place during the training session. The values of each layer might be taken out from previous layer nodes through labelling values to the inputs and feeding them through into the network in order to reach the final output. Alternatively, the value of every hidden network node is calculated using a nonlinear activation function and a linear combination of node values from preceding layers. The value of a network is determined as the optimum of the linear combination of the node from the preceding layer and 0 after an activation function is defined to it [17].

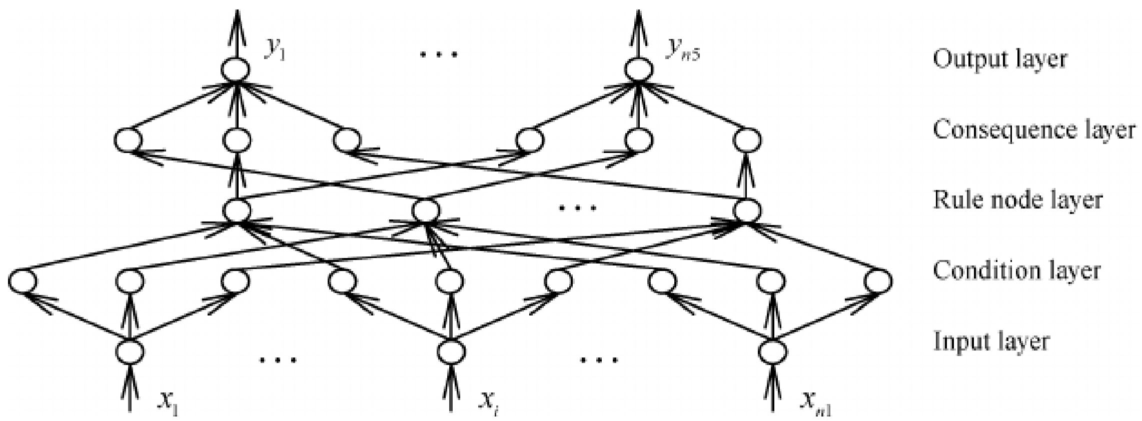

Figure 1. ANFIS layers

DL approaches, such as DNN, are a developing and dominating paradigm for task-driven extracting features from massive amounts of data. This method has shown to be effective in various applications, such as speech processing, computer vision and pattern recognition, finance and investment analysis, text categorization, and robotics. These methodologies are strong, but due of their black-box character, they do not clarify how such feedback is generated, which restricts the applicability of the techniques of deep learning [22]. It is impossible to validate the model's conclusion without first understanding how they arrive at a specific result. Nonetheless, DNN's flaw provided new avenues for academics to investigate alternative viable solutions to the "black-box" problem.

One of several potential methods discovered by scientists was to combine the principles of fuzzy based inference, a knowable rule-based framework, using DNN as a deep neuro-fuzzy system (DNFS) [23]. It has been found that combining fuzzy set theory to deep learning will enhance the levels of models utilizing noisy, diverse, incomplete, or ambiguous input. By employing fuzzy settings or fuzzy logic to determine model parameters, fuzzy systems may be employed as an important element of deep learning techniques [24]. This innovative DNFS method has demonstrated the ability to generate fuzzy rules even without assistance of a human expert, therefore resolving the DNN's "black-box" issue [25]. Moreover, given the same degree of abstraction, the DNFS method outperforms DNN [26], [27]. The capability of fuzzy inference models and deep neural networks has been applied in various ways, even though the idea of DNFS is really quite new [28]. There are three types of DNFS architectures: sequential based, parallel based, and cooperative based. The input supplied to the model passes in a sequential based way using the features of the fuzzy logic system and DNN one by one in a sequential based design. In a parallel architecture, input from fuzzy systems and DNN is evaluated independently before being merged at a point to provide the final result [23]. In the cooperative based approach, fuzzy systems produce fuzzy values from crisp values, which are then sent via a DNN for higher levels of training and abstraction, and a result is formed through making them unfuzzy, which transforms the fuzzy value back into a crisp based output value.

5. Related work

This section discusses in details studies that use fuzzy systems and deep learning mechanism with two fusion and assemble way. Tang *et al.* [29] used 2-minute Based on travel speed data collected from three remote traffic microwave sensors positioned on the southern stretch of a fourth ring road in Beijing City, proposes a new method for creating fuzzy neural networks to predict multi-step travel speed. The Takagi-Sugeno first-order system is used in order to complete the fuzzy inference.

This study introduces a unique convolutional neuro-fuzzy network, which combines fuzzy logic convolutional with neural networks to extract high-level emotion traits from text, audio, and visual input. Using-distributed stochastic neighbor embedding, the feature sets that were generated by fuzzy convolutional layers are compared to the ones extracted by the convolutional neural networks at the same level. This research shows how a multimodal emotion understanding framework can produce new rules for classifying emotions using a flexible neural fuzzy inference system [29].

Creating ANFIS-based models and fine-tuning begin their parameters. Then, utilizing the long short-term memory (LSTM) network structure, building DL-based models and use the grid search approach to improve their parameters. Finally, test all of the suggested models using data from the Intel Berkeley Lab. Experiments show that the suggested models may greatly enhance prediction accuracy and are potentially useful for predicting missing sensor data [29].

Singh *et al.* [30] proposing a solution for NLP combining DNN and fuzzy logics, which is a subset of AI. In India, there are 22 constitutional human languages, while there are nearly 6,909 live human languages worldwide. In reality, building a cross-language machine translation (MT) system is presently not practical due to a lack of resources, knowledge, and other factors. Consider having a large corpus of target and source languages, this proposed system might use neural networks and fuzzy logic to automatically determine the grammatical structure of source sentences that match the destination language. This study deal with flexible machine learning approach that deals with the uncertainty or ambiguity that exists in a system and formulates fuzzy rules to uncover the grammatical construction in new sentences.

Ayeni *et al.* [31] through injecting fuzzy inference systems within deep learning networks, this research proposes a mechanism for implementing rule-based methods into neural networks. Complex issues can be modeled using fuzzy-inference systems and if-then expressions. The physical layers will be infused with fuzzy logic.

Yang *et al.* [32] make a study on growing number of consumer reviews have been made available online. As a result, the NLP community is becoming interested in sentiment categorization for such evaluations. Deep belief networks have been demonstrated to help sentiment analysis in another research DBN. However, identifying the deep network's structure and enhancing its performance is still a work in progress. This research, offer an evolutionary fuzzy deep belief network with rules that are incremental, a complex method based on fuzzy mathematics and genetic algorithms (EFDBNI).

Zhang *et al.* [33] suggested classifier has two features: it employs interpretable linguistic rules for all of the inputs with the same set of linguistic labels, and it has a stacked hierarchical construction of component TSK fuzzy classifiers for high accuracy. The same set of linguistic values is used for all of the inputs and the outputs from previous layers in the stacked hierarchical construction, to provide great interpretability at each layer. The deep shared-linguistic-rule-based TSK fuzzy classifier deep shared-linguistic-rule-based TSK fuzzy classifier (HID-TSK-FC) is a deep TSK fuzzy classifier which is based on shared linguistic fuzzy rules which is highly interpretable. A linguistic rule that has the outputs of the previous layers as inputs can be compared to a fuzzy rule with a nonlinear consequential or a linear consequential with a factor with certainty. Demonstrated that HID-TSK-FC is a mathematically equivalent to a new TSK fuzzy classifier with shared linguistic fuzzy rules. The performance of the HID-TSK-promising FC has been illustrated by intense computational tests on benchmark datasets and a real-world application scenario.

Manogaran *et al.* [34] this research proposes a profound learning strategy which is based on multiple kernel learning (MKL) with ANFIS regarding heart disease detection. The suggested MKL with ANFIS-based profound learning method employs a two-pronged strategy. The MKL technique is used in order to distinguish between healthy people and people who have heart disease. The ANFIS classifier uses the MKL method's output to categorize people with heart disease and those who are healthy. To assess the suggested MKL using ANFIS approach, specificity, sensitivity, and mean square error (MSE) are determined. General discriminant analysis and least square support vector machine (GDA with LS-SVM), principal component analysis (PCA with ANFIS), latent Dirichlet allocation (LDA with ANFIS), and latent Dirichlet allocation (LDA with ANFIS), and latent Dirichlet allocation (LDA with ANFIS). The suggested MKL with ANFIS technique has a high sensitivity as (98%) and specificity as (99%) for the KEGG Metabolic Reaction Network dataset, as well as a low MSE (0.01).

Hatri and Boumhidi [35] consider these learning parameters are controlled using the fuzzy logic, with the aim of reducing the chance of overshooting during the learning process. The suggested incident detection approach has various advantages, including a greater detection rate and a reduced false alarm rate, according to simulation findings.

Wurm *et al.* [36] create intelligent transportation systems, it is necessary to forecast short-term traffic flows. The one model that can keep up with all of the variables. In terms of prediction accuracy, this study looked at the complementarity of non-parametric regression and deep learning. After that, a mixed prediction technique was created by integrating two sub-models based on a fuzzy logic framework.

Hwang *et al.* [37] attempts to autonomously extract polyp characteristics from colonoscopic pictures by utilizing the capabilities of CNN. DL and adaptive regularization approaches are used in the proposed model. The model is divided into two cascaded based encoder-decoder networks, most of which are made up of four CNN layers and two fully connected layers. During segmenting a colonoscopic polyp picture, the front model uses backpropagation learning. Near the end of learning, the output images from either the previous hetero-encoder are considered corrupted labeled images and are fed into the following auto-encoder for denoising learning to improve discriminative power and solve the issue of a lack of class labeled data for medical image tumor tasks. Changing the regularization factor in the loss function using a simple fuzzy logic method will improve the suggested model's performance even further.

Nguyen *et al.* [38] study human emotions through multimodal emotion understanding. Due to the inherent data ambiguity and diversity of video material, emotion interpretation remains a challenge with the rapid growth of video. Despite the fact that deep learning has made significant progress in big data feature learning, it is still seen as deterministic models that are utilized in a "black-box" way and lack the ability to reflect inherent ambiguities in data. Nguyen propose to include the notions of fuzzy logic into the deep learning framework since the possibility theory of fuzzy logic focuses on knowledge representation and reasoning under uncertainty.

Wang *et al.* [39] study using deep learning algorithms and attention from a natural language processing standpoint, efficient sentiment analysis on the internet over such reviews. A complex approach based on deep learning, fuzzy clustering, and information geometry is proposed in this paper. The distribution of training samples is considered as prior knowledge and stored in fuzzy deep belief networks using a better fuzzy C-means (FCM) clustering method. The FCM is improved by using geometry information to establish a geodesic distance between feature distributions for classification. The fuzzy rules learned by FCM are then incorporated into fuzzy deep belief networks based on the clustering findings to improve their performance.

Gangavarapu *et al.* [40] analysis clinical notes contain subjective judgements and vital information about a patient's condition that is lost when transcribed into electronic medical records (EMRs). The structured nature of EMRs is primarily reliant on clinical decision support systems (CDSSs) in the current body of research. Furthermore, there are few studies that attempt to benchmark deep learning models. In this study, intend to construct CDSSs by utilizing the untapped treasure mine of patient-specific information found in unstructured clinical nursing notes. To collect copious clinical documentations of a patient, using a fuzzy token-based similarity technique. Unstructured notes can be organized using topic modelling approaches that capture grammatical and latent semantic information. Furthermore, as an ICD-9 code group, employ deep neural networks' predictive skills for illness prediction.

Hernandez-Julio *et al.* [41] the purpose of this study is to create and assess a method that is able for building data-driven Mamdani-type fuzzy clinical decision support systems through using clusters and pivot tables. The algorithms utilized on five datasets, including Wisconsin, Coimbra breast cancer, wart treatment (Immunotherapy and cryotherapy), and caesarean section, to validate the recommended approach and compare it to previous comparable papers (Literature).

Sadaei *et al.* [42] present a dual approach that relies on fuzzy time series (FTS) and CNN for short-term load forecasting (STLF). As a result, in the proposed approach, multivariate time series data, such as hourly load data, hourly temperature time series, and fuzzified versions of load time series, were translated into multi-channel images and fed to a recommended deep learning CNN model with correct architecture. By using images produced from sequenced values of multivariate time series, the proposed CNN model may detect, and extract connected important parameters in an implicit and automatic manner, without the need for human intervention or expert knowledge. Following this method, it was proved that utilizing the suggested technique is easier than using several common STLF models. As a consequence, one of the most significant distinctions between the proposed methodology and numerous STLF state-of-the-art techniques can be seen. Furthermore, instead of providing one dimension of a time series with precise values, fuzzy logic helps to control over-fitting by displaying it in a fuzzy space, a spectrum, and a shadow. Experiments on test data sets have shown that the suggested technique works.

In modified density peak clustering algorithm (MDPCA) and deep belief networks were used to offer a fuzzy aggregation technique DBNs. MDPCA is used to divide the training set into several subgroups with similar sets of attributes in order to reduce the training set's size and sample imbalance. To train, each subgroup is given its own sub-DBNs classifier. These sub-DBN classifiers are capable of learning and exploring high-level abstract features, automatically reducing data dimensionality, and properly classifying data. The closest neighbor criteria are used to create the fuzzy membership weights of each test sample in each sub-DBNs classifier. The output of all sub-DBNs classifiers is blended using fuzzy membership weights. When evaluated on the NSL-KDD and UNSW-NB15 datasets, our proposed model beats other well-known classification algorithms in terms of overall accuracy, recall, precision, and F1-score. Furthermore, when compared to current intrusion detection approaches, the suggested model outperforms them in terms of accuracy, detection rate, and false positive rate [43], [44].

Gheisarnejad *et al.* [44] this study proposes a novel adaptive controller for air-feed on proton exchange membrane fuel cell (PEMFC) facilities. During the present variation of the PEMFC system, the oxygen excess ratio is initially controlled by a single input interval type-2 fuzzy PI (SIT2-FPI) controller. After that, using the advantages of online learning along with model-free characteristics of reinforcement learning, a deep deterministic policy gradient (DDPG) technique is used to adaptively alter the baseline PI coefficients of the SIT2 controller. An actor-network provides policy signals in the DDPG structure, while a critic-network assesses the quality of the policy given by the actor. The recommended DDPG technique incorporates the baseline PI coefficients into the design objective by default and provides the SIT2-FPI structure additional online coefficient modifying capabilities via learning. The GD approach updates the weights of the actor and critic networks based on reward feedback of the oxygen excess ratio mistake. To verify the adaptability of the DDPG-online SIT2-FPI coefficient adjustment technique, detailed real-time model-in-the-loop (MIL) simulation results and comparative analysis are given.

Mohammadzadeh and Kaynak [45] a robust adaptive control technique for the leader following control of a type of fractional-order multi-agent systems is proposed in this paper (FMAS). A linear matrix inequality (LMI) technique is used to demonstrate asymptotic stability. The actors' nonlinear dynamics are presumed to be unknown. Furthermore, the agents' communication topology is presumed to be unknown and time-varying. To estimate uncertainties, a deep general type-2 fuzzy system (DGT2FS) with restricted Boltzmann machine (RMB) and contrastive divergence (CD) learning technique is presented. According to the simulation findings, the suggested control approach performs well under time-varying architecture, undetermined dynamics, and external disturbances. The suggested DGT2FS's performance is also tested on modelling issues involving high-dimensional real-world statistical models.

Ferdaus *et al.* [46] to apprehend non-supervised temporal characteristics from wind speed data, an interval probability distribution learning (IPDL) model based on constrained Boltzmann machines and rough set theory is suggested in this paper. Using contrastive divergence and Gibbs sampling, the proposed model incorporates a collection of interval latent variables adjusted to reflect the probability distribution of wind speed time series data. For the supervised regression of future wind speed values, a real-valued interval deep belief network (IDBN) is developed using a stack of IPDLs with a fuzzy type II inference system (FT2IS). Our unsupervised feature learning model's great generalization ability, along with the resilience of IPDLs and FT2IS, results in reliable predictions. Simulation findings on the Western Wind Dataset show that single-model techniques, encompassing both surface and subsurface architectures, along with proposed new hybrid strategies, perform much better in 1-h to 24-h forward forecasts.

Beke and Kumbasar [47] the internet of things (IoT) is made up of billions of devices that create massive amounts of data with varying speeds and heterogeneity. Due to a lack of battery capacity, communication failures, and malfunctioning devices in the heterogeneous IoT ecosystem, these sensor-generated data are deemed to be noisy, imprecise, erroneous, and missing. One such research proposes forecasting model regarding deficient sensor data in the IoT ecosystem using DL and ANFIS.

Bai and Dayton [48] data streams are handled through algorithmic development of self-adaptive neuro-fuzzy systems (SANFS) defined by the single-pass learning mode and the open structure property, which allows for effective handling of fast and quickly changing data streams in the fuzzy system community. The underlying bottleneck of SANFSs is due to its design concept, which includes a large number of free parameters (rule premise and rule consequent) that must be adjusted throughout the training process. In the case of a type-2 fuzzy system, this value can potentially double. The parsimonious learning machine (PALM), a revolutionary SANFS, is suggested in this study. PALM employs a novel form of fuzzy rule based on the notion of hyperplane clustering, which drastically decreases the amount of network parameters by eliminating the need for rule premise variables. PALM is suggested for type-1 and type-2 fuzzy systems, both of which are completely dynamic rule-based systems. That is, it can create, merging, and modifying the hyperplane-based fuzzy rule dynamically in a single pass. Furthermore, recurrent PALM is presented as a PALM extension that incorporates the notion of a teacher-forcing process from the deep learning field. In comparison to numerous well-known SANFSs, the suggested model shows considerable improvements in terms of computing complexity and the number of needed parameters, while achieving equivalent and frequently greater prediction accuracy.

Ma *et al.* [49] in this study, we present a novel interval type-2 (IT2) Fuzzy activation layer that is composed of single input IT2 (SIT2) fuzzy rectifying units (FRUs) to improve the learning performances of DNNs. It is concluded that DNNs with SIT have a satisfactory generalization capability, a robust and high learning performance. Guzel *et al.* [50] this research adopts the data set that is publicly available on the internet. it used both feature extraction and deep learning-based classification to detect fake reviews. All of these features will be input to different deep learning models (CNN and RNN). This study then uses fuzzy logic to classify the dataset into 3 groups: fake review, neutral review and true review. This fuzzy classification allows the user to know when a review is real or fake.

Rahimi *et al.* [51] in this research use deep image feature learning with fuzzy rules (DIFL-FR), which combines a rule-based fuzzy modeling technique and a deep learning strategy. The method progressively learns the image features through a layer-by-layer approach based on fuzzy rules so that the feature learning process can be better explained by the generated rules. Extensive experiments are conducted on image datasets of different scales. The results clearly show the effectiveness of the proposed method.

Altameem [52] explore brain connection as a potential approach for exploring brain networks during resting-states or cognitive tasks. The goal of this research is to develop a new way for improving Granger causality, which is one of the most basic approaches for calculating brain effective connection. The suggested model takes advantage of a hierarchical layered structure in which the network's cores are first-order TSK fuzzy rules.

Li *et al.* [53] study bones weakening risk, and night swears symptoms as risk factors for this deadly bone malignancy. These symptoms are difficult to anticipate accurately in the early stages. As a result, an autonomous bone cancer detection system was created in order to anticipate cancer at an earlier stage. The patient's bone pictures are first obtained, and noise in the images is removed using a median filter. After the noise has been removed, the afflicted tumor portion is identified using intuitionistic fuzzy rank correlation. Different statistical characteristics are retrieved from the discovered intuitionistic fuzzy-based clustering pictures. Several deep learning models layers correctly investigate each feature through using Levenberg-Marquardt learning method, and the resulting features are processed as a result.

Kh-madhloom *et al.* [54] Face recognition to identify a specific object is one of the important areas used in research, and it has been widely used in forensic medicine, as the human face contains many parts through which people can be identified through training and analysis, such as lips, forehead, chin, and cheeks, and through which a smile can be detected. This work uses fuzzy logic with deep learning (CNN algorithm) to achieve higher accuracy in smile face.

Khatter and Ahlawat [55] In the process of searching for information on the web, web users have a specific search goal, and the web engine fetches the most relevant information for the search goal, and for this there was a need to enhance the search ability as traditional search algorithms are less efficient in knowing what the user wants compared to machine learning algorithms. In this paper, a search algorithm that links between fuzzy logic and deep learning (using the RNN algorithm) is proposed. The results of using this algorithm showed an increase in accuracy by 94% compared to the traditional search algorithms.

Li *et al.* [56] The natural language-to-logical form difficulty is natural language processing (SQL). This paper presents a demand aggregation-based fuzzy semantic to structured query language (F-SemtoSql) neural method. It addresses sophisticated cross-domain text-to-SQL generation. LSTM and Word2Vec embedding train the corpus as the model's input word vector. SQL statement generation becomes slot filling with the dependency graph method. F-SemtoSql breaks complex jobs into four tiers based on aggregation. We employed the attention mechanism and a fuzzy decision mechanism to improve model decision and prevent the order problem in the classic model. F-SemtoSql leads the Spider text-to-SQL benchmark and the other three datasets with faster convergence.

He *et al.* [57] Rare loss-based risk warning approaches can handle unanticipated emergencies since they ignore real-time data. Machine learning's data processing and real-time computing skills can compensate for traditional risk approaches' inadequacies. Risk analysis can quickly classify process data based on risk. However, labeling risk levels for all operations is too difficult to meet the data requirements for supervised learning. This research develops semi-supervised learning algorithms for real-time risk-based early warning systems. Fuzzy HAZOP quantifies system risk using process data. We use generative adversarial network (GAN)-based semi-supervised learning to identify process risk quickly. To improve warning model generalization, deep network architecture using the convolutional neural network (CNN) codifies multi-dimensional process data. Finally, the proposed approach is tested against other algorithms on a multizone circulating reactor (MZCR).

Sibiya and Sumbwanyambe [58] AI has enabled many plant pathology applications. For plant disease categorization, numerous researchers used pre-trained CNNs including VGG-16, Inception, and Google Net. Some researchers have used AI to classify plant diseases and determine their severity. This paper introduces a new CNN deep learning model to forecast maize common rust disease severity. Threshold-segmentation on photos of infected maize leaves (common rust disease) extracted the percentage of diseased leaf area, which was utilized to develop fuzzy decision rules for assigning common rust images to severity groups. The four severity levels were used to train a VGG-16 network to autonomously classify Common Rust illness test photos. The VGG-16 network's validation accuracy was 95.63% and its testing accuracy was 89% when tested on photos of common rust illness in four severity classes: early, middle, late, and healthy.

Huang *et al.* [59] the goal of this work is to offer a unique strategy that uses CNN deep learning models to forecast the severity of the maize common rust disease. This was conducted through applying a threshold segmentation on photos of infected maize leaves (common rust disease) in order to excerpt the amount of diseased leaf area, in which this would be utilized to create a kind of fuzzy decision rules for assigning prevalent rust images to the sensitivity classes. The four severity classifications were then used to train a VGG-16 network, which was then utilized to automatically categorize the test photos of common rust illness into severity classes. Even before tested on images of the basic rust disease in four stages of severity (early stage, middle stage, late stage, and healthy stage), the VGG-16 network attained a validation accuracy of 95.63% and a testing accuracy of 89 percent once trained to images created and use this proposed approach. The Table 1 includes the summarize studies that use FL and DL.

Table 1. Summarize studies that use FL and DL

Year	Author	Area of publication	Methodology	Result
2017	Tang *et al.* [29]	Traffic prediction	Gaussian fuzzy MF and neural network	Learn quickly
2017	Singh *et al.* [30]	Extracting rule from sentence	Fuzzy logic with DNN	Better performance in extraction
2017	Ayeni *et al.* [31]	Image classification	RNN with fuzzy interface	Better prediction
2018	Yang *et al.* [32]	Sentiment analysis	Fuzzy mathematics with DBN	Better classification Sentiment
2018	Zhang *et al.* [33]	Improving Takagi-Sugeno-Kang	Linguistic rules FL with DL	Higher performance
2018	Manogaran *et al.* [34]	Heart diagnosis for disease	FL with ANFIS	Better diagnosis
2018	Hatri and Boumhidi [15]	Traffic detection	Stacked auto-encoder with back-propagation algorithm and FL	Improve incident detection
2019	Wurm *et al.* [36]	Traffic prediction	Use of FL, CNN, LSTM	Increased precision and robustness
2019	Hwang [37]	Segmentation of images (medical)	Fuzzy with CNN	Detecting polyps with greater accuracy
2019	Nguyen *et al.* [38]	Emotion extraction from text, sound, video	Fuzzy with CNN	Excellent emotional feature extraction
2019	Wang *et al.* [39]	Sentiment analysis	Fuzzy clustering with DBN	Better classification Sentiment
2019	Gangavarapu *et al.* [40]	Classification clinical automotive for note	Fuzzy similarity with Doc2Vec DL	Better prediction
2019	Julio *et al.* [41]	Clinical classification	Fuzzy logic with DNN	Better classification
2019	Sadaei *et al.* [42]	Short-term prediction	FL with CNN	Better prediction
2019	Yang *et al.* [43]	Intrusion detects	Weight based FL with DBN	Better detection
2019	Gheisarnejad *et al.* [44]	Fuel sensors control	FL with DNN	Better control
2019	Mohammadzadeh and Kaynak [45]	Agent controlling Fractional-based	FL with RBM	Better performance
2019	Ferdaus *et al.* [46]	Data stream	(SANFS), FL	Better accuracy
2019	Beke and Kumbasar [47]	IoT prediction	Linguistic variable FL with ANFIS, LSTM	Better prediction
2019	Bai and Dayton [48]	Stream regression for data	Neuro-fuzzy with adaptive DL	Improve computation time
2019	Ma *et al.* [49]	Improve learning DNN Performance	Interval Fuzzy activation layer for DNN	Better performance DNN
2019	Guzel *et al.* [50]	sentiment analysis (reviews businesses)	CNN, RNN and FL	Better classification
2019	Rahimi *et al.* [51]	Extract feature from image	Fuzzy rule, DNN	Better learning
2020	Altameem [52]	Estimation of non-linear efficient connectivity	Takagi–Sugeno– Kang method associated with DBN, Linear Granger	Superiority when it comes to detecting effective connection
2020	Li *et al.* [53]	bone cancer classification	Intuitionistic fuzzy and DNN	Higher prediction and low effect in segmentation
2020	Kh-madhloom *et al.* [54]	Face smile recognition	Fuzzy logic with CNN	Higher recognition accuracy
2020	Khatter and Ahlawat [55]	Smile detection from faces	Fuzzy logic with RNN	Higher recognition
2020	Li *et al.* [56]	Personalized web searching	Fuzzy logic with DL	Better classification
2020	He *et al.* [57]	Convert Text-to-SQL	CAN with fuzzy logic	Better convergence
2021	Sibiya and Sumbwanyambe [58]	Control wind turbines	FL AND DL	Improve wind speed
2021	Huang *et al.* [59]	Rust disease prediction	Thresholding DL with logic-based fuzzy	Better prediction

6. NEED, LIMITATIONS, AND IMPACTS

This study will have an impact on the usage of the deep learning models, as the researchers will use the deep learning based on fuzzy logic to improve the performance of the deep learning. Although this paper has many limitations, such as: it does not apply deep learning, fuzzy logic, or the hybrid model to the actual aforementioned applications to prove that the hybrid model will improve the performance of deep learning. The results will be analyzed extensively by employing statistical metrics including F-score, Precision and Recall.

7. DISCUSSION

DL has a high level of learning ability and has a significant impact on the advancement of AI. the other hand, they are critical in clarifying the inexact and vague concepts that are predominant in the current world. The benefits of both deep learning algorithms and fuzzy systems are combined in research on the fusion of deep learning and fuzzy systems. They not only give a very accurate learning or prediction system, but they also eliminate unpredictability.

The benefits of integrating fuzzy systems in terms of performance might be better used. Deep learning is a hot field of research, and the performance gains that may be gained by combining fuzzy systems should be taken advantage of more. Deep learning has two significant drawbacks at the moment. To begin with, training a deep neural network requires a sufficient amount of time. The second issue is the illustration of deep neural networks. Despite the fact that calculus-based training techniques are now widely used in the sector of training, they do not guarantee optimality. Moreover, the process of understanding how the input is transferred to the output in a neural network is challenging.

Additional drawbacks are data noise vulnerability, as well as the difficulty in dealing with diverse or missing data. To illustrate the advanced analysis, recent aids on the integration of deep learning and fuzzy systems are presented. To begin, the fuzzy community has been introduced to two aspects of deep learning: statistical data from relevant publications on the merger of DL and fuzzy systems, and standard deep learning methodologies. This is a growing study topic that is generating a lot of attention. After that, the combination of DL and fuzzy systems was investigated further.

To overcome these problems, the majority of research today focuses on using fuzzy systems. Integrating fuzzy theory with deep learning has been found to enhance the productivity of models with noisy, diverse, partial, or inaccurate input. Fuzzy systems might be used as a significant part in deep learning models by employing fuzzy variables or fuzzy logic in order to determine training parameters. The use of fuzzy systems may increase the computational difficulty. The presence of software applications speeds up deep learning procedures even further. Platforms for fuzzy logic systems, on the other hand, are few. Despite the fact that the models claim to be noise resistant, Despite the fact that the models are noise resistant and search throughout a broader area without being stuck in local optima, calculating the fuzzy parameters takes a lengthy time with both the present architectures.

Traditional deep learning models are also used in combination with FL. They would be used in order to process both input and output data. In models, fuzzy inputs may be integrated with traditional DL models such as deep belief network (DBN) and convolutional neural network (CNN). The results of the networks may also be fuzzed. This allows us to use the software platforms to hurry the training of DNN using fuzzy systems. Data fuzzification, on the other hand, is frequently reliant on the quality of the information, making it more difficult to create a general model.

For a high-level overview, this study created a fusing framework and visual form, and evaluated the present status of several types of fuzzy techniques that are used in deep learning, as well as some reasons why fuzzy techniques are used in deep learning and the combining application areas. Fuzzy systems have major impacts on deep learning frameworks in terms of classification, prediction accuracy, estimation, NLP, auto-based control, and other areas. According to recent contributions, fusion is used in a variety of fields, including but not limited to computer science, natural language processing, smart energy management systems, medical systems, and the machine and equipment industry. Furthermore, while addressing potential future challenges, the fusion technology as well as the application possibilities of the fusion methods will be thoroughly examined. Whereas the fusion of DL and FL improves the predictive model or accuracy rate once compared with traditional DL models, there are still a few restrictions in terms of computation time, understandability, input parameters, and original input constraints, which somewhat give a detailed understanding of the fusion. As a consequence, more study into enhancing the efficiency of fuzzy deep learning models may be conceivable in the future. Deep learning using fuzzy systems has been shown to be resistant to noise, so it may be used to defend against adversarial assaults.

8. CONCLUSION

This survey paper reviews some of the deep learning-based fuzzy logic models and techniques that were presented and proposed in previous studies, where fuzzy logic is used to improve deep learning performance. First, the deep learning models can be applied in many applications: self-driving cars, sentiment analysis, virtual assistants, social media, healthcare, and more. Second, fuzzy logic can also be applied in several applications, such as automobile manufacturing, the aviation sector, applications in the home and more. Then, to improve the results and the performance of the deep learning, we can apply a hybrid deep neuro-fuzzy system between ANFIS and DNN classifiers. Finally, in conclusion, the combination of deep learning and fuzzy systems shows a thorough study effort in both the principle and application arenas. As science and technology advance, deep learning utilizing fuzzy systems may become more important in artificial intelligence. In future work, we plan to apply this hybrid model to certain classification tasks like the sentiment analysis task to classify the text with either positive or negative sentiment.

REFERENCES

[1] D. S. W. Ting *et al.*, "Artificial intelligence and deep learning in ophthalmology," *British Journal of Ophthalmology*, vol. 103, no. 2, pp. 167–175, Feb. 2019, doi: 10.1136/bjophthalmol-2018-313173.

[2] P. Ongsulee, "Artificial intelligence, machine learning and deep learning," in *2017 15th International Conference on ICT and Knowledge Engineering (ICT&KE)*, 2017, pp. 1–6, doi: 10.1109/ICTKE.2017.8259629.

[3] T. J. Sejnowski, "The unreasonable effectiveness of deep learning in artificial intelligence," *Proceedings of the National Academy of Sciences*, vol. 117, no. 48, pp. 30033–30038, Dec. 2020, doi: 10.1073/pnas.1907373117.

[4] I. Arel, D. C. Rose, and T. P. Karnowski, "Deep machine learning - a new frontier in artificial intelligence research," *IEEE Computational Intelligence Magazine*, vol. 5, no. 4, pp. 13–18, Nov. 2010, doi: 10.1109/MCI.2010.938364.

[5] R. Gupta, D. Srivastava, M. Sahu, S. Tiwari, R. K. Ambasta, and P. Kumar, "Artificial intelligence to deep learning: machine intelligence approach for drug discovery," *Molecular Diversity*, vol. 25, no. 3, pp. 1315–1360, Aug. 2021, doi: 10.1007/s11030-021-10217-3.

[6] D. M. Dimiduk, E. A. Holm, and S. R. Niezgoda, "Perspectives on the impact of machine learning, deep learning, and artificial intelligence on materials, processes, and structures engineering," *Integrating Materials and Manufacturing Innovation*, vol. 7, no. 3, pp. 157–172, 2018, doi: 10.1007/s40192-018-0117-8.

[7] F. Wang, X. Diao, S. Chang, and L. Xu, "Recent progress of deep learning in drug discovery," *Current Pharmaceutical Design*, vol. 27, no. 17, pp. 2088–2096, May 2021, doi: 10.2174/1381612827666210129123231.

[8] J. Sanchez-Juarez, M. Granados-Baez, A. A. Aguilar-Lasserre, and J. Cardenas, "Intelligent decision support system (IDSS) to optimize 2D materials detection using digital image processing and deep learning," in *2021 Conference on Lasers and Electro-Optics (CLEO)*, 2021, pp. 1–2.

[9] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning representations by back-propagating errors," *Nature*, vol. 323, no. 6088, pp. 533–536, Oct. 1986, doi: 10.1038/323533a0.

[10] G. E. Hinton and R. R. Salakhutdinov, "Reducing the dimensionality of data with neural networks," *Science*, vol. 313, no. 5786, pp. 504–507, Jul. 2006, doi: 10.1126/science.1127647.

[11] D. Bonanno, K. Nock, L. Smith, P. Elmore, and F. Petry, "An approach to explainable deep learning using fuzzy inference," in *Proc. of SPIE*, May 2017, pp. 1–5, doi: 10.1117/12.2268001.

[12] E. Hüllermeier, "Does machine learning need fuzzy logic?," *Fuzzy Sets and Systems*, vol. 281, pp. 292–299, Dec. 2015, doi: 10.1016/j.fss.2015.09.001.

[13] L. A. Zadeh, "A fuzzy-algorithmic approach to the definition of complex or imprecise concepts," *International Journal of Man-Machine Studies*, vol. 8, no. 3, pp. 249–291, May 1976, doi: 10.1016/S0020-7373(76)80001-6.

[14] S. R. Price, S. R. Price, and D. T. Anderson, "Introducing fuzzy layers for deep learning," in *2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, Jun. 2019, pp. 1–6, doi: 10.1109/FUZZ-IEEE.2019.8858790.

[15] M. Ghomshei, "Fuzzy logic in engineering education and evaluation of graduate attributes," in *Proceedings of the Canadian Engineering Education Association (CEEA)*, Dec. 2018, pp. 1–4, doi: 10.24908/pceea.v0i0.13094.

[16] D. Ruta and B. Gabrys, "An overview of classifier fusion methods," *Computing and Information Systems*, vol. 7, pp. 1–10, 2000.

[17] G. S. Osipov, A. I. Panov, and K. S. Yakovlev, *Artificial intelligence*, vol. 11866. Cham: Springer International Publishing, 2019.

[18] N. Talpur, S. J. Abdulkadir, H. Alhussian, M. H. Hasan, N. Aziz, and A. Bamhdi, "A comprehensive review of deep neuro-fuzzy system architectures and their optimization methods," *Neural Computing and Applications*, vol. 34, no. 3, pp. 1837–1875, 2022, doi: 10.1007/s00521-021-06807-9.

[19] Y. Zheng, Z. Xu, and X. Wang, "The fusion of deep learning and fuzzy systems: A state-of-the-art survey," *IEEE Transactions on Fuzzy Systems*, vol. 30, no. 8, pp. 2783–2799, Aug. 2022, doi: 10.1109/TFUZZ.2021.3062899.

[20] R. R. Yager and L. A. Zadeh, *An introduction to fuzzy logic applications in intelligent systems*. Boston, MA: Springer US, 1992.

[21] Z. Wang, P. A. Keane, M. Chiang, C. Y. Cheung, T. Y. Wong, and D. S. W. Ting, "Artificial intelligence and deep learning in ophthalmology," in *Artificial Intelligence in Medicine*, Cham: Springer International Publishing, 2021, pp. 1–34.

[22] N. Talpur, S. J. Abdulkadir, and M. H. Hasan, "A deep learning based neuro-fuzzy approach for solving classification problems," in *2020 International Conference on Computational Intelligence (ICCI)*, Oct. 2020, pp. 167–172, doi: 10.1109/ICCI51257.2020.9247639.

[23] L. A. Zadeh, "Fuzzy logic and approximate reasoning," *Synthese*, vol. 30, no. 3–4, pp. 407–428, 1975, doi: 10.1007/BF00485052.

[24] S. Banerjee, S. K. Singh, A. Chakraborty, A. Das, and R. Bag, "Melanoma diagnosis using deep learning and fuzzy logic," *Diagnostics*, vol. 10, no. 8, Aug. 2020, doi: 10.3390/diagnostics10080577.

[25] W. Kwon, Y. Jin, D. Kang, and S. Lee, "Affine memory control for synchronization of delayed fuzzy neural networks," *IEEE Access*, vol. 9, pp. 5140–5149, 2021, doi: 10.1109/ACCESS.2020.3048170.

[26] R. Das, S. Sen, and U. Maulik, "A survey on fuzzy deep neural networks," *ACM Computing Surveys*, vol. 53, no. 3, pp. 1–25, May 2021, doi: 10.1145/3369798.

[27] Y.-J. Zheng, W.-G. Sheng, X.-M. Sun, and S.-Y. Chen, "Airline passenger profiling based on fuzzy deep machine learning," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 28, no. 12, pp. 2911–2923, Dec. 2017, doi: 10.1109/TNNLS.2016.2609437.

[28] S. Rajurkar and N. K. Verma, "Developing deep fuzzy network with Takagi Sugeno fuzzy inference system," in *2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, Jul. 2017, pp. 1–6, doi: 10.1109/FUZZ-IEEE.2017.8015718.

[29] J. Tang, F. Liu, Y. Zou, W. Zhang, and Y. Wang, "An improved fuzzy neural network for traffic speed prediction considering periodic characteristic," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 9, pp. 2340–2350, Sep. 2017, doi: 10.1109/TITS.2016.2643005.

[30] S. P. Singh, A. Kumar, H. Darbari, A. Rastogi, and S. Jain, "Extract reordering rules of sentence structure using neuro-fuzzy machine learning system," in *2017 International Conference On Smart Technologies For Smart Nation (SmartTechCon)*, Aug. 2017, pp. 173–177, doi: 10.1109/SmartTechCon.2017.8358364.

[31] B. K. Ayeni, J. B. Sahalu, and K. R. Adeyanju, "Detecting cross-site scripting in web applications using fuzzy inference system," *Journal of Computer Networks and Communications*, pp. 1–10, Aug. 2018, doi: 10.1155/2018/8159548.

[32] P. Yang, D. Wang, X.-L. Du, and M. Wang, "Evolutionary DBN for the customers' sentiment classification with incremental rules," in *Advances in Data Mining. Applications and Theoretical Aspects*, 2018, pp. 119–134.

[33] Y. Zhang, H. Ishibuchi, and S. Wang, "Deep Takagi–Sugeno–Kang fuzzy classifier with shared linguistic fuzzy rules," *IEEE Transactions on Fuzzy Systems*, vol. 26, no. 3, pp. 1535–1549, Jun. 2018, doi: 10.1109/TFUZZ.2017.2729507.

[34] G. Manogaran, R. Varatharajan, and M. K. Priyan, "Hybrid recommendation system for heart disease diagnosis based on multiple kernel learning with adaptive neuro-fuzzy inference system," *Multimedia Tools and Applications*, vol. 77, no. 4, pp. 4379–4399, Feb. 2018, doi: 10.1007/s11042-017-5515-y.

[35] C. El Hatri and J. Boumhidi, "Fuzzy deep learning based urban traffic incident detection," in *2017 Intelligent Systems and Computer Vision (ISCV)*, Apr. 2017, pp. 1–6, doi: 10.1109/ISACV.2017.8054903.

[36] M. Wurm, P. Dangelo, P. Reinartz, and H. Taubenbock, "Investigating the applicability of cartosat-1 DEMs and topographic maps to localize large-area urban mass concentrations," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 7, no. 10, pp. 4138–4152, Oct. 2014, doi: 10.1109/JSTARS.2014.2346655.

[37] M. Hwang *et al.*, "An adaptive regularization approach to colonoscopic polyp detection using a cascaded structure of encoder–decoders," *International Journal of Fuzzy Systems*, vol. 21, no. 7, pp. 2091–2101, Oct. 2019, doi: 10.1007/s40815-019-00694-y.

[38] T.-L. Nguyen, S. Kavuri, and M. Lee, "A multimodal convolutional neuro-fuzzy network for emotion understanding of movie clips," *Neural Networks*, vol. 118, pp. 208–219, Oct. 2019, doi: 10.1016/j.neunet.2019.06.010.

[39] M. Wang, Z.-H. Ning, T. Li, and C.-B. Xiao, "Information geometry enhanced fuzzy deep belief networks for sentiment classification," *International Journal of Machine Learning and Cybernetics*, vol. 10, no. 11, pp. 3031–3042, Nov. 2019, doi: 10.1007/s13042-018-00920-3.

[40] T. Gangavarapu, A. Jayasimha, G. S. Krishnan, and K. S. Sowmya, "TAGS: Towards automated classification of unstructured clinical nursing notes," in *Natural Language Processing and Information Systems*, 2019, pp. 195–207.

[41] Y. F. Hernández-Julio, M. J. Prieto-Guevara, W. Nieto-Bernal, I. Meriño-Fuentes, and A. Guerrero-Avendaño, "Framework for the development of data-driven mamdani-type fuzzy clinical decision support systems," *Diagnostics*, vol. 9, no. 2, May 2019, doi: 10.3390/diagnostics9020052.

[42] H. J. Sadaei, P. C. de Lima e Silva, F. G. Guimarães, and M. H. Lee, "Short-term load forecasting by using a combined method of convolutional neural networks and fuzzy time series," *Energy*, vol. 175, pp. 365–377, May 2019, doi: 10.1016/j.energy.2019.03.081.

[43] Y. Yang, K. Zheng, C. Wu, X. Niu, and Y. Yang, "Building an effective intrusion detection system using the modified density peak clustering algorithm and deep belief networks," *Applied Sciences*, vol. 9, no. 2, Jan. 2019, doi: 10.3390/app9020238.

[44] M. Gheisarnejad, J. Boudjadar, and M.-H. Khooban, "A new adaptive type-II fuzzy-based deep reinforcement learning control: Fuel cell air-feed sensors control," *IEEE Sensors Journal*, vol. 19, no. 20, pp. 9081–9089, Oct. 2019, doi: 10.1109/JSEN.2019.2924726.

[45] A. Mohammadzadeh and O. Kaynak, "A novel general type-2 fuzzy controller for fractional-order multi-agent systems under unknown time-varying topology," *Journal of the Franklin Institute*, vol. 356, no. 10, pp. 5151–5171, Jul. 2019, doi: 10.1016/j.jfranklin.2019.05.006.

[46] M. M. Ferdaus, M. Pratama, S. G. Anavatti, and M. A. Garratt, "PALM: An incremental construction of hyperplanes for data stream regression," *IEEE Transactions on Fuzzy Systems*, vol. 27, no. 11, pp. 2115–2129, Nov. 2019, doi: 10.1109/TFUZZ.2019.2893565.

[47] A. Beke and T. Kumbasar, "Learning with type-2 fuzzy activation functions to improve the performance of deep neural networks," *Engineering Applications of Artificial Intelligence*, vol. 85, pp. 372–384, Oct. 2019, doi: 10.1016/j.engappai.2019.06.016.

[48] J. Bai and M. S. Dayton, "A system using deep learning and fuzzy logic to detect fake yelp reviews," Master Thesis, University of Dayton, 2019.

[49] X. Ma, Z. Deng, P. Xu, K.-S. Choi, D. Wu, and S. Wang, "Deep image feature learning with fuzzy rules," *arXiv:1905.10575*, May 2019.

[50] M. Guzel, I. Kok, D. Akay, and S. Ozdemir, "ANFIS and deep learning based missing sensor data prediction in IoT," *Concurrency and Computation: Practice and Experience*, vol. 32, no. 2, Jan. 2020, doi: 10.1002/cpe.5400.

[51] M. Rahimi, R. Davoodi, and M. H. Moradi, "Deep fuzzy model for non-linear effective connectivity estimation in the intuition of consciousness correlates," *Biomedical Signal Processing and Control*, vol. 57, Mar. 2020, doi: 10.1016/j.bspc.2019.101732.

[52] T. Altameem, "Fuzzy rank correlation-based segmentation method and deep neural network for bone cancer identification," *Neural Computing and Applications*, vol. 32, no. 3, pp. 805–815, Feb. 2020, doi: 10.1007/s00521-018-04005-8.

[53] Q. Li, W. LI, W. Sun, J. Li, and Z. Liu, "Fingerprint and assistant nodes based Wi-Fi localization in complex indoor environment," *IEEE Access*, vol. 4, pp. 2993–3004, 2016, doi: 10.1109/ACCESS.2016.2579879.

[54] J. Kh-madhloom, A. Diwan, and Z. A. Abdulhussein, "Smile detection using convolutional neural network and fuzzy logic," *Journal of Information Science and Engineering*, vol. 36, no. 2, pp. 269–278, 2020, doi: 10.6688/JISE.202003_36(2).0007.

[55] H. Khatter and A. K. Ahlawat, "An intelligent personalized web blog searching technique using fuzzy-based feedback recurrent neural network," *Soft Computing*, vol. 24, no. 12, pp. 9321–9333, Jun. 2020, doi: 10.1007/s00500-020-04891-y.

[56] Q. Li, L. Li, Q. Li, and J. Zhong, "A comprehensive exploration on spider with fuzzy decision text-to-SQL model," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 4, pp. 2542–2550, Apr. 2020, doi: 10.1109/TII.2019.2952929.

[57] R. He, X. Li, G. Chen, G. Chen, and Y. Liu, "Generative adversarial network-based semi-supervised learning for real-time risk warning of process industries," *Expert Systems with Applications*, vol. 150, Jul. 2020, doi: 10.1016/j.eswa.2020.113244.

[58] M. Sibiya and M. Sumbwanyambe, "Automatic fuzzy logic-based maize common rust disease severity predictions with thresholding and deep learning," *Pathogens*, vol. 10, no. 2, Jan. 2021, doi: 10.3390/pathogens10020131.

[59] K. Huang, Y. Zhang, H. D. Cheng, P. Xing, and B. Zhang, "Semantic segmentation of breast ultrasound image with fuzzy deep learning network and breast anatomy constraints," *Neurocomputing*, vol. 450, pp. 319–335, Aug. 2021, doi: 10.1016/j.neucom.2021.04.012.

BIOGRAPHIES OF AUTHORS

Dhafar Fakhry Hasan is Teaching at the College of Medicine-University of Mosul. She obtained her B.Sc. (1998) in computer science, M.Sc. (2004) in computer science and she Ph.D. student in AI She published many researches Her research interests include AI, image processing, computer networks, data base. She can be contacted at email: dhafar.allayla@gmail.com, dhf@uomosul.edu.iq. https://www.researchgate.net/profile/Dhafar-Allayla.

AbdulSattar Mohammed Khidhir is an assistant professor at Mosul Technical Institute-Northern Technical University in Iraq. He obtained his B.Sc. (1981), M.Sc. (1989) and Ph.D. (2000) in Electronics and communications engineering from University of Mosul. He supervised many Ph.D. and M.Sc. theses in different scientific and engineering areas. He was a member of scientific committees for many Ph.D. and M.Sc. students. He published many researches in various fields of science and engineering (see google scholar). He reviewed many scientific papers for journals and conferences. He can be contacted at email: abdulsattarmk@ntu.edu.iq, abdulsattarmk@gmail.com.