Engineering and Technology Journal e-ISSN: 2456-3358

Volume 09 Issue 06 June-2024, Page No.- 4231-4240

DOI: 10.47191/etj/v9i06.09, I.F. – 8.227

Review: Deep Learning and Fuzzy Logic Applications

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ABSTRACT: The modeling and prediction field bosses a variety of practical applications, deep learning is a powerful tool used in this field. It has been proved that deep learning is a useful technique for extracting extremely accurate predictions from complex data sources, and also Recursive neural networks have demonstrated their usefulness in language translation and caption production, but convolutional neural networks remain the dominant solution for image classification tasks. In addition, deep learning, also known as deep neural networks, involves training models with multiple layers of interconnected artificial neurons. The primary idea of deep learning is to learn data representations through raising levels of abstraction. These strategies are effective, but they don't explain how the result is produced. Without knowing how a solution is arrived at using deep learning. In the field of artificial intelligence, deep learning and fuzzy logic are two powerful techniques. In addition, fuzzy logic combines deep learning will help deep learning select the desired features and work without supervision, this will make it possible to develop reliable systems with rich DL information even in the absence of hand-labeled data. Fuzzy logic that interpreted these features will subsequently provide explanations for the system's choice of classification label. This survey highlights the various applications which use fuzzy logic to improve deep learning.

KEYWORDS: deep learning, neural network, fuzzy logic, artificial intelligence, optimization method, machine learning, learning model.

1. INTRODUCTION

In machine learning, the progress of deep learning has become a significant research area in all facets of life. It has several applications such as natural language processing, image processing, precision medicine, self-driving cars, and speech recognition, however those models continue as black boxes, which represent an important barrier to the extensive distribution of deep learning technology, thus many users will not be trusted a model whose solutions ambiguous (cannot be explained) (Mu & Zeng, 2019). Deep neural networks use sequential layers of nonlinear processing to extract features from dataset and they are a category of machine learning model. Nevertheless, the training of deep learning networks is very mathematically intensive, and it uses for widely utilized optimization techniques that do not ensure optimal performance. Moreover, such networks do not work well in areas where data are insufficient and sensitive to noise in data. One way to help understand neural networks is to extract rules. Therefore, deep learning and fuzzy logic contributes to solving complex problems and making more accurate predictions (Shinde & P, 2018). These studies will help the researchers of fuzzy logic to solve complex problems of artificial intelligence and improve the applications in machine learning. Recent years, there are several a number of literature work in this domain (Yang et al., 2020). During the 2019, presented a paper of major study, they found insert a new fuzzy layer to be used for deep learning. This fuzzy layer has the advantage of being able to be embedded anywhere in the network, highly flexible. In addition, it can implement any fuzzy gathering method like Sugueno fuzzy and the Choquet integrals. This study introduces a deep learning approach that incorporates fuzzy techniques that is based the implementation of semantic partition utilizing per-pixel classification. Tests are carried out on a standard data set. Also, a data set gathered at a U.S. Army location by an unmanned aerial system for the purpose of automatically segmenting roads, and the early results are encouraging (Price et al., 2019). In 2021, demonstrated a hybrid system that combines deep learning and deep learning fuzzy logic controller as well as two neural networks. To calculate the current wind and predict the future wind, deep learning algorithms are applied. Evaluation and prediction were combined to identify the efficient wind to support the fuzzy logic. An improvement has been achieved with 21% acquired regard to the PID controller, and 7% regard to the criterion fuzzy controller (this is respecting for medium and low wind speeds). The use of technology in medical diagnosis and patient care is not an easy task that is performed by professional developers (Sierra-Garcia et al.,2021). This technology is used to improve medical decision taking treatment choices and improve a person's health, on 2021 Modem A. Reddy and coworkers displayed proposed Deep Learning Neuron-Fuzzy classification method. The proposed system is utilized evaluating a patient data based with over twenty input features based on COVID-19 symptoms. In addition, to develop the classification technique and make it more accurate, the results are compared with many deep learning and Neuro-Fuzzy method (Reddy et al.,2021). The results of this study could be used in the detection of other diseases by increasing the number of input parameters. (El Hatri et al.,2018) were presented approach of deep learning method with a stacked auto-encoders devise for automatic TID trouble. This system utilized unsupervised learning method to rehabilitate the deep neuron network. To action the fine setting step, the back-propagation algorithm is utilized precisely control the deep network's parameters. In addition, in order that reduce the possibility, of overtaking through the learning process, reduce error, and raise convergence speed, fuzzy logic is used to control the learning parameters. Experiment results indicate FDNN comparing to DNN reduce the training time by 28.19% and decrease the error, also FDNN in conditions of indices of performance is exceed SLNN and MLNN, as well DNN in conditions of the speed of convergence, making it an effective learning mechanism for TID.

2. APPLICATIONS

1.1 Fuzzy Rules Extraction from Deep Neural Networks

This article to provide the basic methods from neural network that can help in the issue of extracting rules. Some recent algorithms discussed from each category have been named as analytical, pedagogical, eclectic, and decomposition. The three criteria described are the focus of this article. We focus on algorithms that do not require special requirements on how to extract the rules before train the neural network (WCraven &WShavlik,1994). This study introduces methods have a high level of generality, these algorithms that are able of extracting rules from direct multiplication neural networks. This study uses algorithms such as the KT algorithm, rule extractor via decision tree and Tsukimoto's polynomial algorithm. In addition, the basic problems that appear from extracting rules from neural networks and the methods for solving them (Averkin & Yarushev, 2021).

1.2 Fuzzy Logic and Deep Learning Integration in Likert Type Data

Deep learning networks display a high-performance level and have a wide range of applications. Despite this, it is still possibly making some decisions by examining the attitude of the network in tests. This paper is present a study to analyse the performance of deep learning algorithms using a 5-point Likert-type scale. It integrated the deep learning and fuzzy logic algorithms, by converting the data groups into a fuzzy logic form-utilizing trapezium or triangular fuzzy data (Deng & Pei , 2009). The satisfaction estimation problem was selected, to examine the performance of the design. Fuzzy number data sets that reach three or four times at minimum for many parameters than regular data sets. Artificial data was created in the experimental study; this data is used for the experimental investigation to thoroughly examine the effectiveness of classification model performance under various conditions. In oppose to the literature, the fuzzy numbers produced a single-outcome series during the performance of a deep learning model (ÜNAL & ÇETİN, 2022). Figure1. demonstrates a logistic regression model using data from atriangular fuzzy
Likert type.

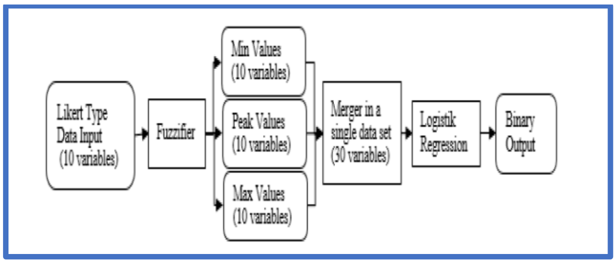

Figure1. Triangular Fuzzy Likert-Type Data with a logistic regression method.

2.3 convolutional neural network and fuzzy logic-based hybrid melanoma diagnosis system

Early detection of melanoma cancer creates a greater chance of treatment. Medical statistics have appeared that the life rates depend greatly on the phase of the cancer. Therefore, diagnosis systems that depend on Computer such as machine learning algorithms help early-stage detection highly (Yalcinkaya & Erbas, 2021). The current study combined fuzzy logic with AlexNet, and the three parameters obtained were specificity (0.82), accuracy (0.80), and sensitivity (0.54). These parameters were used as inputs of the AlexNet system via a fuzzy correlation map. The proposed system work on the melanoma pictures to remove the high-grade medical picture requirement to train the network. In addition, this system has been developed to be able to extract data that is not visible in pixels and surrounding areas. A deep CNN (Convolutional neural network) requires a huge of data to process to obtain of reliable result. Nevertheless, to acquire and utilize the desired adequate data for illnesses is not efficient of time and cost. Therefore, the proposed fuzzy logic-based fuzzy correlation map is solving the limitedness of training data set (Pomponiu et al., 2016). Figure 2. displays the basic structure of the designed fuzzy logic model and the changed AlexNet based CNN.

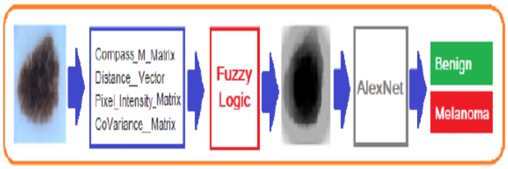

Figure 2. The developed fuzzy logic system's basic architecture and the modified CNN built on AlexNet.

2.4 Hybrid Mamdani Fuzzy Rules and Convolutional Neural Networks for Analysis and Identification of Animal Images

Although it is difficult to recognition of animal pictures and classify them in fast way for several practical applications. This study proposed precise, fast, and automatic processes for finding and classifying various picture of animals. It uses A hybrid model of convolutional neural networks (CNNs) and Mamdani Type-2 fuzzy rules. This study utilizes about 27,307 images. The hybrid system uses the CNN paradigm for the object's class after using the fuzzy logic rules to detect the images (Russakovsky et al., 2015). More than 21,846 images of animals were utilized to train and evaluate the CNN model. The proposed system is more precise due to the double adaptively, and the system removes the unnecessary data to decrease CNN layers, which result it less training time. In addition, the experimental results of the system gained high performance; high accuracy for recognizing moving objects of 98% and a mean square error less compared other studies (Mohammed & Hussain, 2021). Figure 3. demonstrates the suggested hybrid Mamdani fuzzy and CNN network and. Figure 4. displays results identification samples made with the hybrid CNN with Mandani fuzzy.

Figure 3. Training the suggested CNN and Mamdani fuzzy hybrid network.

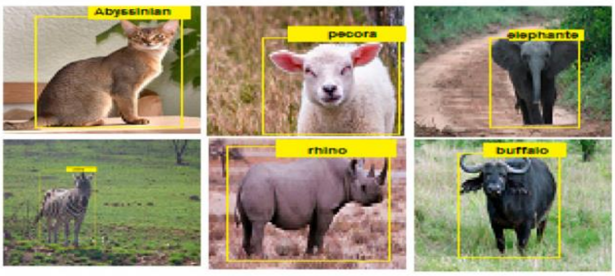

Figure 4. results of employing a hybrid CNN with the Mandani fuzzy rule for sample recognition.

2.5 Quality control system by means of CNN and fuzzy systems

Quality examination processes in typical crop collection centers are held by workers, due to different situations such as work stress, personal problems or fatigue, deviate their concept in relation to the quality of a product. So, the systems of automatic quality operations in industry is take a great importance in industrial production operations (Chow et al., 2012). This system is focused on the extraction of features and classification by means of artificial intelligence techniques. The system suggested for the extraction of features in each of its parameters (weight, equatorial diameter, and harmed area) worked properly, and the image processing was sufficiently strong in the specified environment. Despite, there were issues with ambient lighting because the lemon bark easily creates a reflection on its surface, creating fictitious defects like lemon 6. The suggested fuzzy system consistently classified three classes for each lemon, according to the features and rules determined for the estimation of these, according to quality standards. The results show acquisition scores averaging 98.25% for the classification of the fresh lemons and 93.73% for the decayed lemons, allowing for the disposal, at an early stage, of those lemons that were not directly appropriate for consumption. This lead is reducing the processing times in another stage (Enciso-Aragon et al., 2018). Figure 5. shows the general scheme of the algorithm.

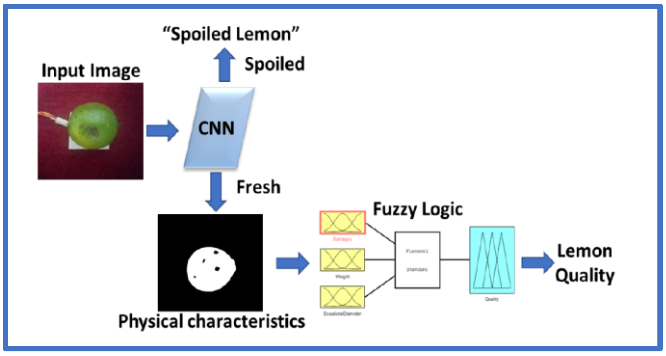

Figure 5. basic scheme of the algorithm.

2.6 Adaptive Probabilistic Neuro-Fuzzy System and its Hybrid Learning in Medical Diagnostics Task

There are many limitations in real-world tasks, for example, the problem of medical diagnosis task in environment of restricted dataset and nested categories The lack of extensive training data through real-world activities, especially in the medical diagnosis task, indicates the inability to use the mathematical system for deep learning. In addition, there were other factors, like in a dataset; data can be differently scaled: in numerical interval, nominal and binary, numerical ratios, ordinal (ordered). This lead does not permit the utilize of well-known neural networks. In order that beat problems and constraints, the adaptive neuro-fuzzy system has been suggested (Berka et al.,2009). The hybrid system is distinguished from both the traditional shallow and deep multilayer networks that it allows the processing of a large amount of dataset within the whole problem of data flow extraction. In addition, it contains the present a limited number of neural networks in the fuzzy layer with a high rate of learning. System combines membership functions and learning of its parameters. Also, this system is combined based on the concept "Neurons at data points" be-tween a teacher, lazy learning and self- learning based on the idea of

"Winner takes all”. Additionally, this system enables the resolution of diagnostic tasks in requirements long and short for training datasets and mutually nested classes (Bodyanskiy et al.,2021**)**. Figure 6. demonstrates design of probabilistic neuro-fuzzy system.

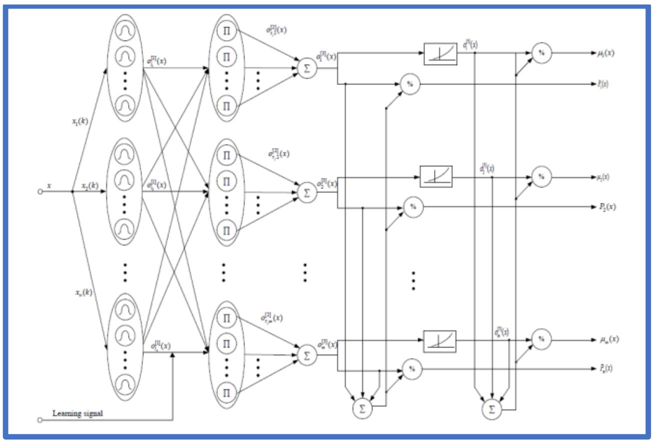

Figure 6. demonstrates design of probabilistic neuro-fuzzy system.

2.7 Fuzzy Logic Approximation and Deep Learning Neural Network for Fish Concentration Maps

The application of ultrasound is one of the important and widespread appli cations to solve various applied problems, including the detection of underwater objects, to formalize it using artificial intelligence algorithms, the experience, and expertise of professionals in the interpretation of echolocation data. This paper proposes use the algorithm of fuzzy logic and CNN YOLO v2, based on the results of ultrasound data processing, to obtain maps of fish intensification, pographic maps of lakes, and a map of hunter location. This algorithm uses sonar images for find of classes like “bottom fish”, “grass”, “predator”, “fish”, “school of fish”. The algorithm involved the following steps: dividing the input frame into nested blocks, utilizing CNN YOLO v2 for block handling, and extracted bounding boxes were integrated around each item, incorporating the fish concentration map (Kim &Yu,2016) . This method has an accuracy of 70.1% and the false positive results has low percentage in state of fish existence. Also, to improve the precision of the method we need considerably expand the dataset for neural network training (Mäkiö et al.,2019).

2.8 Optimization Based Fuzzy Deep Learning Classification for Sentiment Analysis

The paper presents various sentimental analyses have been reviewed by using fuzzy neural network methods. The suggested system solves the misclassification issue in the twitter review data set by using a convolution neutral network with a developmental improved technique. In addition, the technique works to solve the gap of more precise detection with relevant emotion in text. Also, he feed fore networks has ability excerption the logical characteristics of an emoji in a phrase, so the work utilizes deep learning board optimization techniques. The feature vectors used bigram and unigram models, and those are input into LSTM and CNN for learning (Uma et al.,2020).

2.9 Energy-efficient cluster-based unmanned aerial vehicle networks with deep learning-based scene classification model.

Researchers and academics have given significant interest to unmanned aerial vehicles (UAVs). Unmanned vehicles have been applied in many applications like Disaster administration, wildlife observation and surveillance, intelligent transportation system. This study presents to solve location classification from UAV-captured high-resolution remote sensing photos (Pustokhina et al.,2021).

This proposed project utilized collecting with parameter tuned residual network (C-PTRN) as a model that is included in the proposal. It comprises two main phases: cluster creation and scene categorization. At the second phase, a deep learning based ResNet50 approach is used to scene classification. These results showed that the C-PTRN design had the highest accuracy (95.69%), recall (98.91%), and F score (96.54%) of any model tested (Alzenad et al.,2017).

2.10 Semantic segmentation of breast ultrasound image with fuzzy deep learning network and breast anatomy constraints

One of the most significant illnesses impacting women's health is breast cancer. Breast ultrasound (BUS) imaging is generally widely used method to initial breast cancer diagnosis due to its low cost, lack of radiation but it is low resolution and weak quality. This paper suggested semantic segmentation approach which it consists of two components: fuzzy completely convolutional network and based on breast anatomy restrictions, it uses precisely fine-tuning post-processing. To get substantially better outcomes, the suggested strategy addresses the following problems.1) fuzzy logic is utilized for deal with the uncertainty in the original picture and feature maps that it generated from convolutional layers.2) in addition, more information can obtain from fuzzy method.3) To accomplish better results, a novel membership function Sigmoid function is uitlilzed.4) the uncertainty mapping function is intended to make the mixture of fuzzy and non-fuzzy information more acceptable (Huang et al.,2021). The suggested approach accomplished state-of-the-art achievement compared with that of present ways. It has an actual positive percentage of 90.33%, false 9.00%, and junction over union (IoU) 81.29% (Xian et al.,2018). Figure 7. shows the structure of the proposed fuzzy FCN.

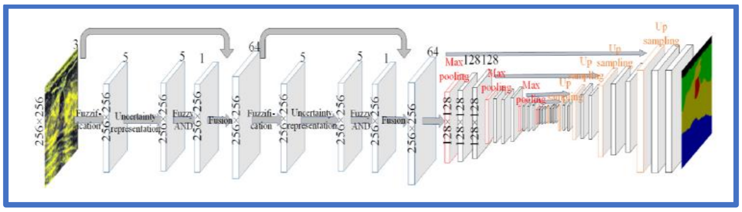

Figure 7. Structure of the proposed fuzzy FCN.

2.11 ECG-Based Driver's Stress Detection Using Deep Transfer Learning and Fuzzy Logic Approaches

The driver exposed for prolonged may lead to traffic accidents and deterioration of the driver's health condition. In addition, traditional machine learning approaches are heavily used in previous work in this area. It is always difficult to get the best features using these approaches. CNN on the basis of deep learning techniques have been extensively applied for stress modeling (de Naurois et al.,2019). In this article, were suggested pre-trained networks (Google Net, DarkNet-53, ResNet-101, InceptionResNetV2, Xception, DenseNet-201, and InceptionV3) using scalogram images in order to increase the detection performance automatically and minimize computation time and cost. This pre-trained network on the basis of Convolutional Neural Networks (CNN) are utilized to classification the three stages of stress skilled by the driver. Using a normalized Continuous Wavelet Transform (CWT), the time-recurrence ECG elements for the three stress stages are achieved as scalogram pictures. Model 5 based upon Xception surpasses Google Net, InceptionResNetV2, InceptionV3, DarkNet-53, DenseNet-201, ResNet-101 based models by 11.32%, 7.54%, 1.88%, 11.32%,9.45%, and 5.66%, respectively, and accomplished 98.11% total verification accuracy, according to the results (Amin et al.,2022). Figure 8. shows the system architecture.

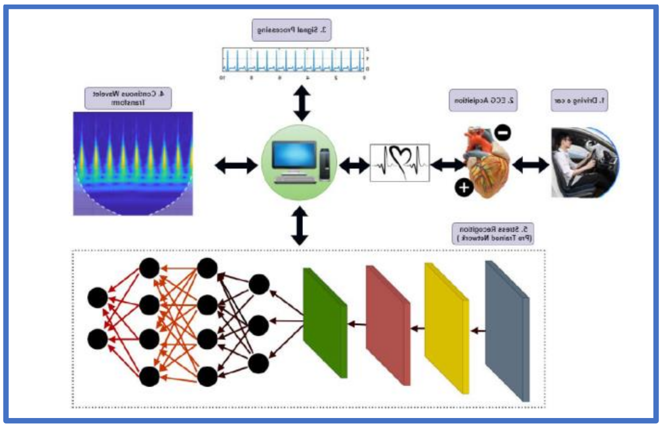

Figure 8. System architecture.

2.12 Crowd Emotion Prediction for Human-Vehicle Interaction through Modified Transfer Learning and Fuzzy Logic Ranking

Modern technology is required in a smart city to predict inhabitant behavior. Transportation systems observe and analyze people behavior to enhance traffic flow around the city. This study presents a novel approach to evaluate crowd condition, which extends the range of interactions between human and vehicle.

The study employed UAVs, S MS, and fuzzy logic estimations to determine the optimal path to take when there is heavy traffic. The improved ResNet model employs fuzzy reasoning to anticipate crowd sentiments in both low and high crowding situations (Nayak et al., 2021). In addition, the obtained frames from the UAV are undergo to a new deep transfer learning (DTL) approach in order to enhance making decisions. The obtained results A 98.5% accuracy rate, good performance and the suggested integrated model's attributes are population behavior sturdiness. UAVs, CAVs, and fuzzy logic evaluations work together to determine the best pathway. UTS systems can more accurately evaluate traffic flow by utilizing drones to detect aberrant patterns of activity and report them to the appropriate authorities (Khosravi et al.,2023). Figure 9. illustrates how fuzzy logic evaluations, CAVs, and UAVs collaborate.

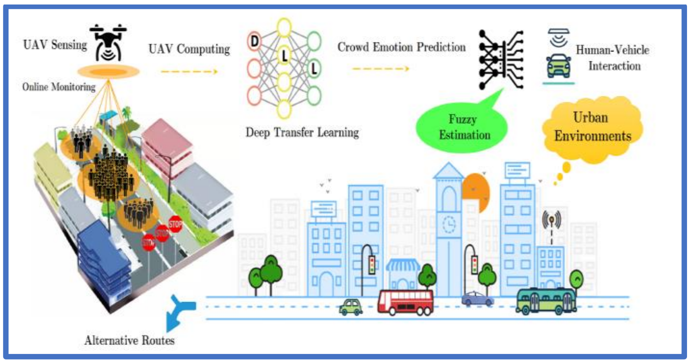

Figure 9. Fuzzy estimation, UAVs, and CAVs collaborate to determine the best pathway.

2.13 Adaptive Fuzzy Logic Deep-Learning Equalizer for Mitigating Linear and Nonlinear Distortions in Underwater Visible Light Communication

There are many advanced technologies that apply communications systems in underwater environments, these underwater environments may be as unknown and dangerous as the seas. UVLC systems are an important technology for transmitting signals in aquatic environments, although it faces problems like linear and nonlinear distortions. This paper uses AFL-DLE (an adaptable fuzzy logic deep-learning equalizer) to reduce linear and nonlinear aberration. In order to enhance overall system performance, the proposed AFL-DLE makes use of the improved Chaotic Sparrow Search Optimization method (ECSSOA) (Ali et al.,2022). In addition,it utilizes constellation partitioning algorithms and complex-valued neural networks. According to the experimental findings, the suggested AFL-DLE was successful in achieving the desired bit error rate of 55% and distortion rate of 45%, as well as in lowering computing cost (75%), increasing transmission rate (99%), and decreasing computational complexity (48%). The suggested system, when compared to other methods, is more efficient. The efficacy and practicality of the AFL-DLE in real-world applications have made internet data processing possible in high-speed UVLC methods (Rajalakshmi et al.,2023). Figure 10. shows the architectural of the suggested AFL-DLE.

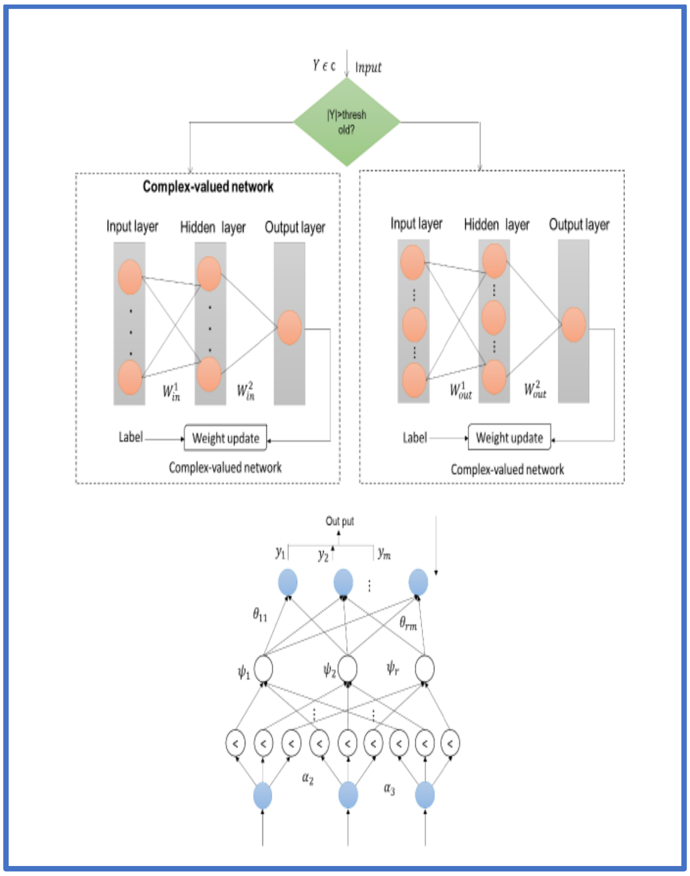

Figure 10. The AFL-DLE's architectural design.

2.14 Fuzzy Logic with Deep Learning for detection of Skin Cancer

In recent decades, the incidence of skin cancer has increased significantly. The visual similarity to benign lesions makes the diagnosis of skin cancer a difficult task. This paper uses a modified deep learning model and fuzzy logic-based picture segmentation for skin cancer diagnosis. In order to improve the segmentation findings, the study aims to improve dermoscopic images by pre-processing methods, mathematical logic infusion, standard deviation approaches, and the left-right fuzzy method. The goal of these pre-processing procedures is to help the visible of lesion. This process is occurred by eliminating artifacts like hair follicles and dermoscopic scales (Sahnoun et al.,2017). After that, the image is improved by applying the histogram equalization technique, and it is segmented using the recommended way prior to the detection step. Moreover, the upgraded YOLO classifier, which has greater depth and can link multi-label features to give improved and more precise results, classifies the segmented lesion picture. From the results obtained, it was shown that Yellow provides a better faster and accuracy than most of the previous classifiers. The study proposed utilizing the ISIC (2017, 2018) data sets, as well as 2000 and 8695 picture to train the classifier. In addition, to test the proposed algorithm, datasets were utilized PH2(Singh et al., 2023).

Figure 11. displays a flowchart of the suggested approach for melanoma digital diagnosis.

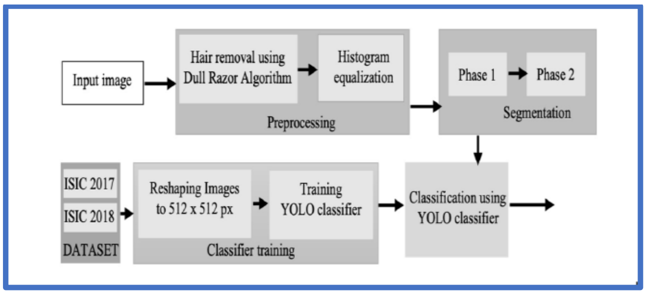

Figure 11. Flowchart of melanoma digital diagnosis.

2.15 An optimized fuzzy deep learning model for data classification based on NSGA-II

In practical applications, like management systems, engines, financial models, and image processing, deep learning and fuzzy logic have been used to overcome uncertainty in data. In this work, an optimized fuzzy deep learning (OFDL) model based on Non-Dominated Sorting Genetic Algorithm is proposed for data categorization. In multi-modal learning, OFDL uses the NSGA-II to improve the structure of DL and fuzzy learning. OFDL finds the best trade-offs between two contradictory target methods in order to best feature selection, increase accuracy and reduce the number of features. After that, OFDL utilized Pareto optimal solutions to improve multiple objectives by using NSGA-I is based on their thematic functions in order to achieve the fuzzy membership functions and optimal back propagation (Mi et al.,2022). OFDL When compared to fuzzy classifiers, the analysis of OFDL demonstrates high performance in terms of F-measure, recall, precision, accuracy, and Rate of true positives. Moreover, OFDL outperforms previous fuzzy DNN models in classification tasks in terms of accuracy (Yazdinejad et al.,2023).

3. REFERENCE CATEGORIZATION

Table 1: lists the literature review; many projects and researchers are focused on fuzzy logic and deep learning.

No.	Title	Year	Accuracy	Dataset	Ref
1	Automatic Fingerprint Classification System Using Fuzzy Neural Techniques	2022	FNN: 98.5%	NIST-4	[37]
2	Fingerprint matching and correlation check-ing using level 2 features	2017		NIST DB4 and FVC 2004	[38]
3	Multimodal Biometric System Fusion Using Fingerprint and Face with Fuzzy Logic	2017	99.5	FV C2002 + Face94	[39]

4	Damaged Fingerprint Classification by Deep Learning with Fuzzy Feature Points	2016		FVC2004	[40]
5	Hybrid Mamdani Fuzzy Rules and Convolu-tional Neural Networks for Analysis and Identi-fication of Images	2021	Type-2 fuzzy (CNNs) :98٪		[41]
6	Fuzzy based Pooling in Convolutional Neural Network for Image Classification	2021	0.944	MNIST, CIFAR-10	[42]
7	Fuzzy Logic Module of Convolutional Neural Network for Handwritten Digits Recognition	2016	99%		[43]
8	Interpretable Machine Learning: Convolutional Neural Networks with RBF Fuzzy Logic Classification Rules	2018	96%	MNIST	[44]
9	Integration of fuzzy logic and a convolutional neural network in three-way decision-making	2022			[45]
10	A Survey on Fuzzy Deep Neural Networks	2020			[46]
11	A Deep neuro-fuzzy network for image classification	2019	TSK model: 99.58%, 88.18%	MNIST, CIFAR-10	[47]
12	Fuzzy Pooling	2020			[48]
13	A fuzzy convolutional neural network for enhancing multi-focus image fusion	2022	FCNN		[49]
14	A comprehensive review of deep neuro-fuzzy system architectures and their optimization methods	2021			[50]
15	Hierarchical Fuzzy Deep Learning for Image Classification	2022		YaleB database	[51]
16	Applications of Deep Learning and Fuzzy Systems to Detect Cancer Mortality in Next-Generation Genomic Data	2020			[52]
17	Analysis, Processing, and Applications of Fuzzy System and Deep Learning	2022			[53]
18	A fuzzy-enhanced deep learning approach for early detection of Covid-19 pneumonia from portable chest X-ray images	2022	81%		[54]
19	A novel fuzzy-based ensemble model for load forecasting using hybrid deep neural networks	2020			[55]
20	Applications of Deep Learning and Fuzzy Systems to Detect Cancer Mortality in Next-Generation Genomic Data	2020			[56]

4. CONCLUSION

Deep learning algorithms is widely used to the study and analysis of dig data because it has accomplished huge success in widely of applications such as computer vision, computer games, speech recognition, and natural language processing. This paper introduces deep learning and fuzzy logic applications and points up related grouping of deep learning and fuzzy logic.

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