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Bridging Techniques: A Review of Deep Learning and Fuzzy Logic Applications

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Abstract

The modelling and prediction field boasts various practical applications, such as deep learning, which is a powerful tool used in this field. It has been proved that deep learning is a valuable technique for extracting extremely accurate predictions from complex data sources. Recursive neural networks have also demonstrated usefulness in language translation and caption production. However, 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 rising levels of abstraction. These strategies are effective but do not 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 to help deep learning select the desired features and work without supervision, making it possible to develop reliable systems with rich DL information even without hand-labelled data. Fuzzy logic that interprets these features will subsequently explain 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.

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, representing an important barrier to the extensive distribution of deep learning technology. Thus, many users will not be trusted with a model whose solutions are ambiguous (cannot be explained) (Mu & Zeng, 2019). Deep neural networks use sequential layers of nonlinear processing to extract features from datasets, and they are a category of machine learning models. Nevertheless, the training of deep learning networks is very mathematically intensive, and it is used 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 contribute to solving complex problems and making more accurate predictions (Shinde & P, 2018). These studies will help researchers of fuzzy logic solve complex problems of artificial intelligence and improve the applications of machine learning. In recent years, several works of literature have been in this domain (Yang et al., 2020). In 2019, Price presented a paper on inserting a new fuzzy layer for deep learning (Price et al., 2019). 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 incorporating fuzzy techniques for implementing semantic partition utilizing per-pixel classification. Tests are carried out on a standard data set. Also, an unmanned aerial system gathered a data set at a U.S. Army location to segment roads automatically, and the early results were encouraging (Price et al., 2019). Soft Computing is an approach that provides cost-effective solutions for real-world problems using neural networks, fuzzy systems, and evolutionary computation (Kazem et al., 2016). Various image enhancement techniques are deployed to improve image quality, covering a range of methods, basic filtering techniques, and more advanced algorithms in different applications like image classification and prediction (Al-Hatmi & Yousif, 2017). A Deep Convolutional Neural Network (DCNN) is an artificial neural network that processes and analyses visual data, such as images. This network has layers that automatically learn to recognize features like edges, textures, and patterns in data. It works like the human visual system, gradually identifying more complex features as the data moves through the network (Alkishri et al., 2023). In 2021, a hybrid system that combines deep learning and deep learning fuzzy logic controllers and two neural networks was demonstrated. Deep learning algorithms are applied to calculate the current wind and predict the future wind. Evaluation and prediction were combined to identify the efficient wind and support fuzzy logic. An improvement has been achieved, with 21% acquired about the PID controller and 7% regarding the criterion fuzzy controller (this is respecting medium and low wind speeds). Using technology in medical diagnosis and patient care is not an easy task performed by professional developers (Sierra-Garcia et al., 2021). This technology is used to improve medical decision-making treatment choices and a person's health; in 2021, Modem A. Reddy and coworkers displayed a proposed Deep Learning Neuron-Fuzzy classification method. The proposed system evaluates patient data based on over twenty input features based on COVID-19 symptoms. In addition, the results are compared with many deep learning and Neuro-Fuzzy methods to develop the classification technique and make it more accurate (Reddy et al., 2021). The results of this study could be used to detect other diseases by increasing the number of input parameters. (El Hatri et al., 2018) The deep learning method was approached with a stacked auto-encoder device for automatic TID trouble. This system utilized unsupervised learning methods to rehabilitate the deep neuron network. The back-propagation algorithm controls the deep network's parameters precisely to take action in the OK setting step. In addition, fuzzy logic controls the learning parameters to reduce the possibility of overtaking through the learning process, reduce error, and raise convergence speed. Experiment results indicate FDNN, compared to DNN, reduces the training time by 28.19% and decreases the error. Also, FDNN in conditions of performance indices exceeds SLNN and MLNN, and DNN in conditions of speed of convergence, making it an effective learning mechanism for TID.

2. Literature Survey

In this literature survey reviews notable works integrating deep learning and fuzzy logic techniques, highlighting their applications and performance metrics. The survey covers studies spanning various domains, focusing on image classification, biometric systems, and healthcare diagnostics.

Mohamed (2022) developed an automatic fingerprint classification system leveraging fuzzy neural techniques. Using the NIST -4 dataset, they achieved an impressive accuracy of 98.5%. This study underscores the efficacy of combining fuzzy logic with neural networks to enhance fingerprint classification accuracy (Mohamed & Nyongesa, 2022). Ezhilmaran (2017) explored fingerprint matching and correlation checking, utilising level 2 features with the NIST DB4 and FVC 2004 datasets. Although the study does not specify accuracy, it contributes valuable insights into improving fingerprint recognition systems through detailed feature analysis (Ezhilmaran and Adhiyaman, 2017). Sharma (2017) proposed a multimodal biometric system that integrates fingerprint and face recognition with fuzzy logic, achieving 99.5% accuracy using the FVC2002 and Face94 datasets. This work demonstrates the potential of multimodal systems in enhancing biometric authentication reliability (Sharma and Singh, 2017). Wang (2016) also investigated the classification of damaged fingerprints using deep learning combined with fuzzy feature points, utilising the FVC2004 dataset. Although the accuracy has yet to be reported, the study highlights methods to handle suboptimal fingerprint conditions (Wang et al., 2016).

Hybrid Mamdani Fuzzy Rules and Convolutional Neural Networks for Analysis and Identification of Images is presented by Mohammed and Hussain (2021). They combined Type-2 fuzzy logic with Convolutional Neural Networks (CNNs), achieving 98% image analysis and identification accuracy. This hybrid approach showcases the robustness of integrating fuzzy logic with CNNs for image-processing tasks (Mohammed and Hussain, 2021). Sharma et al. (2019) introduced a fuzzy-based pooling method in CNNs for image classification, achieving a 94.4% accuracy on MNIST and CIFAR-10 datasets. This study suggests that fuzzy-based pooling can significantly enhance the performance of standard CNN architectures. Popko and Weinstein incorporated a fuzzy logic module into CNNs for recognising handwritten digits, reporting 99% accuracy (Sharma, et al., 2019). This integration exemplifies the effectiveness of fuzzy logic in refining CNNs for specific recognition tasks. Xi and Panoutsos (2018) proposed using Radial Basis Function (RBF) fuzzy logic classification rules within CNNs, achieving a 96% accuracy on the MNIST dataset. This approach enhances interpretability in machine learning models while maintaining high performance. Subhashini et al. integrated fuzzy logic with CNNs for three-way decision-making, though the study does not specify accuracy metrics. This integration is pivotal for enhancing decision-making frameworks in complex scenarios (Xi & Panoutsos, 2018). Das (2020) provided a comprehensive survey on fuzzy deep neural networks, covering various architectures and applications. It is a foundational reference for understanding the intersection of fuzzy logic and deep learning (Das et al., 2020). Yazdanbakhsh and Dick (2019) developed a deep neuro-fuzzy network, reporting accuracies of 99.58% on MNIST and 88.18% on CIFAR-10. Their model demonstrates the potential of neuro-fuzzy systems to achieve high accuracy in image classification tasks (Yazdanbakhsh & Dick, 2019). Diamantis and Iakovidis (2020) introduced the concept of fuzzy pooling within CNNs, although specific accuracy metrics have yet to be reported. This innovation highlights a novel approach to enhancing CNN performance through fuzzy logic (Diamantis & Iakovidis, 2020). Bhalla et al. (2022) proposed a fuzzy convolutional neural network (FCNN) for multi-focus image fusion, enhancing image quality without specific accuracy metrics. This study illustrates the application of fuzzy logic in improving image fusion techniques (Bhalla et al., 2022). Talpur et al. (2021) reviewed various deep neuro-fuzzy system architectures and their optimisation methods, thoroughly analysing existing methodologies and their effectiveness (Talpur et al., 2021). Kamthan et al. (2022) explored hierarchical fuzzy deep learning for image classification using the YaleB database, emphasising the hierarchical approach's benefits without specifying accuracy metrics (Kamthan et al., 2022).

Yang et al. (2020) applied deep learning and fuzzy systems to detect cancer mortality using genomic data, highlighting the integration's potential in healthcare diagnostics without detailed accuracy metrics (Yang et al., 2020). Seongsoo and Young (2022) discussed the analysis, processing, and various applications of fuzzy systems combined with deep learning, providing insights into their practical implementations and benefits (Seongsoo & Young, 2022). Ieracitano et al. (2022) developed a fuzzy-enhanced deep-learning method for early COVID-19 pneumonia detection, achieving 81% accuracy. This study demonstrates the crucial role of fuzzy logic in enhancing deep learning models for medical diagnostics (Ieracitano et al., 2022). Sideratos et al. (2020) proposed a fuzzy-based ensemble model for load forecasting, combining hybrid deep neural networks. This work highlights the application of fuzzy logic in improving predictive models in energy management (Sideratos et al., 2020).

3. Applications of Deep Learning and Fuzzy Logic

3.1. Fuzzy Rules Extraction from Deep Neural Networks

Craven and Shavlik provide the basic methods from neural networks that can help extract 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 to extract the rules before training the neural network (Craven & Shavlik, 1994). The Averkin & Yarushev study introduces methods with a high level of generality; these algorithms can extract rules from direct multiplication neural networks. This study uses the KT algorithm, rule extractor via decision tree and Tsukimoto's polynomial algorithm. In addition, the fundamental problems that appear from extracting rules from neural networks and the methods for solving them (Averkin & Yarushev, 2021).

3.2. 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, making some decisions by examining the network's attitude in tests is still possible. This paper presents a study to analyse the performance of deep learning algorithms using a 5-point Likert-type scale. It integrated deep learning and fuzzy logic algorithms by converting the data groups into a fuzzy logic form, utilising 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. Unlike 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 a triangular fuzzy Likert type.

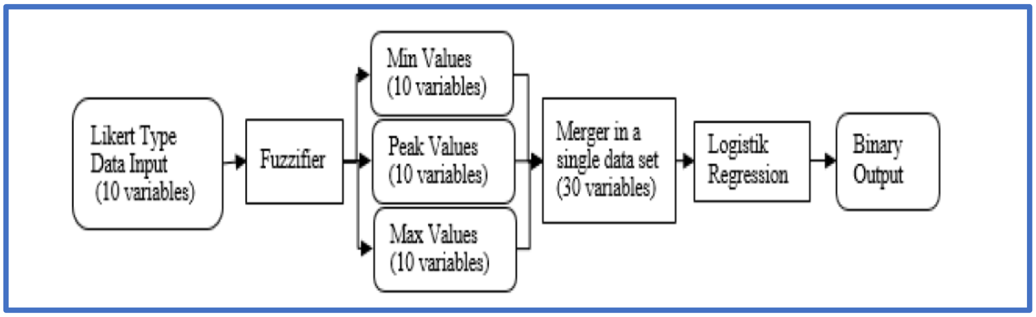

Figure1. Triangular Fuzzy Likert-Type Data with a logistic regression method.

3.3. CNN and fuzzy logic-based hybrid melanoma diagnosis system

Early detection of melanoma cancer creates a greater chance of treatment. Medical statistics have shown that life rates depend significantly on the phase of the cancer. Therefore, diagnosis systems that depend on Computers, 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 works on 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 considerable data to process for reliable results. Nevertheless, acquiring and utilizing the desired adequate data for illnesses could be more efficient in terms of time and cost. Therefore, the proposed fuzzy logic-based fuzzy correlation map solves the limitedness of the 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.

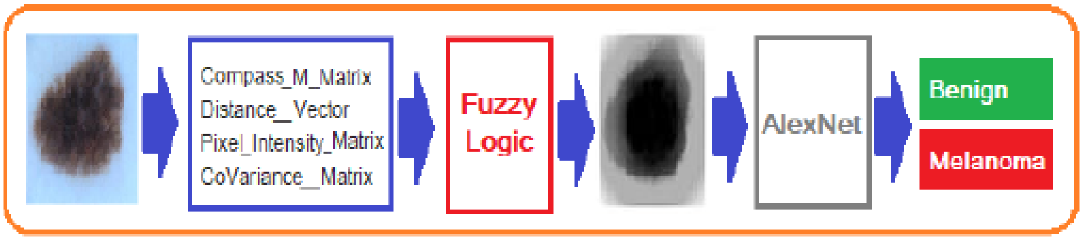

Figure 2. The developed fuzzy logic system's basic architecture and the modified CNN built on AlexNet.

3.4. Hybrid Mamdani Fuzzy Rules and CNN for Identifying Animal Images

Although it is challenging to recognise animal pictures and classify them in a fast way for several practical applications, this study proposed precise, fast, and automatic processes for finding and classifying various pictures of animals. It uses A hybrid model of convolutional neural networks (CNNs) and Mamdani Type-2 fuzzy rules. This study utilises 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 utilised to train and evaluate the CNN model. The proposed system is more precise due to the double adaptivity, and the system removes the unnecessary data to decrease CNN layers, which results in less training time. In addition, the experimental results of the system gained high performance and accuracy for recognising moving objects of 98% and a mean square error compared to other studies (Mohammed & Hussain, 2021). Figure 3. demonstrates the suggested hybrid Mamdani fuzzy and CNN network. Figure 4. displays the results of identification samples made with the hybrid CNN with Mandani fuzzy.

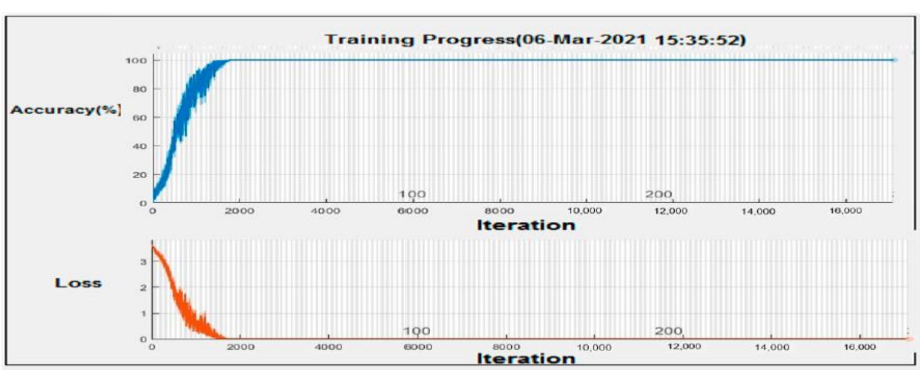

Figure 3. Training the suggested CNN and Mamdani fuzzy hybrid network.

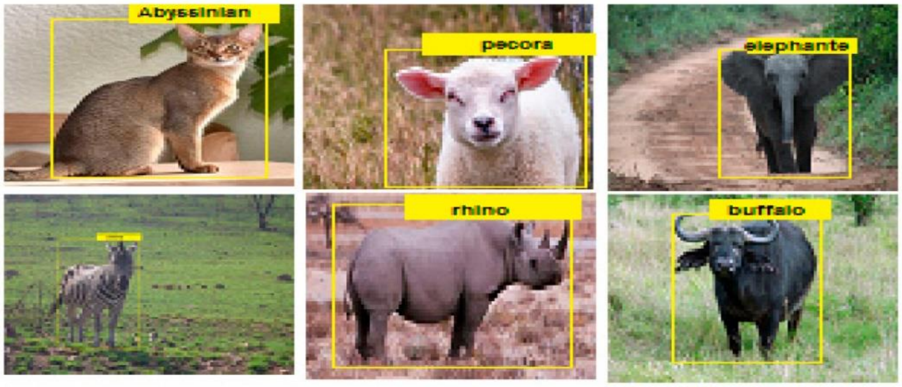

Figure 4. results of employing a hybrid CNN with the Mandani fuzzy rule for sample recognition.

3.5. Quality control system by means of CNN and fuzzy systems

Quality examination processes in typical crop collection centres are held by workers due to different situations such as work stress, personal problems or fatigue, deviating their concept about the quality of a product. So, the systems of automatic quality operations in the industry take great importance in industrial production operations (Chow et al., 2012). This system is focused on the extraction of features and classification using artificial intelligence techniques. The system suggested for extracting features in each parameter (weight, equatorial diameter, and harmed area) worked adequately, and the image processing was sufficiently strong in the specified environment. Despite this, 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 estimating 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 early disposal of those lemons that were not directly appropriate for consumption. This leads to reducing the processing times in another stage (Enciso-Aragón et al., 2018). Figure 5. shows the general scheme of the algorithm.

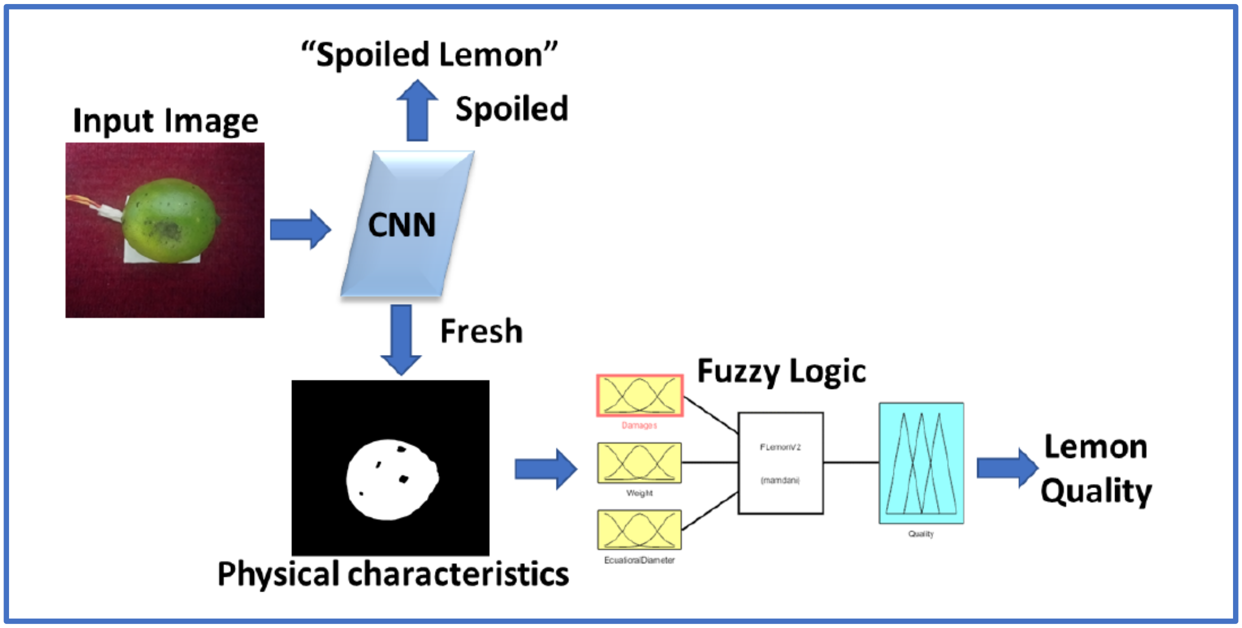

Figure 5. basic scheme of the algorithm.

3.6. Adaptive Probabilistic Neuro-Fuzzy System in Medical Diagnostics Task

The 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.

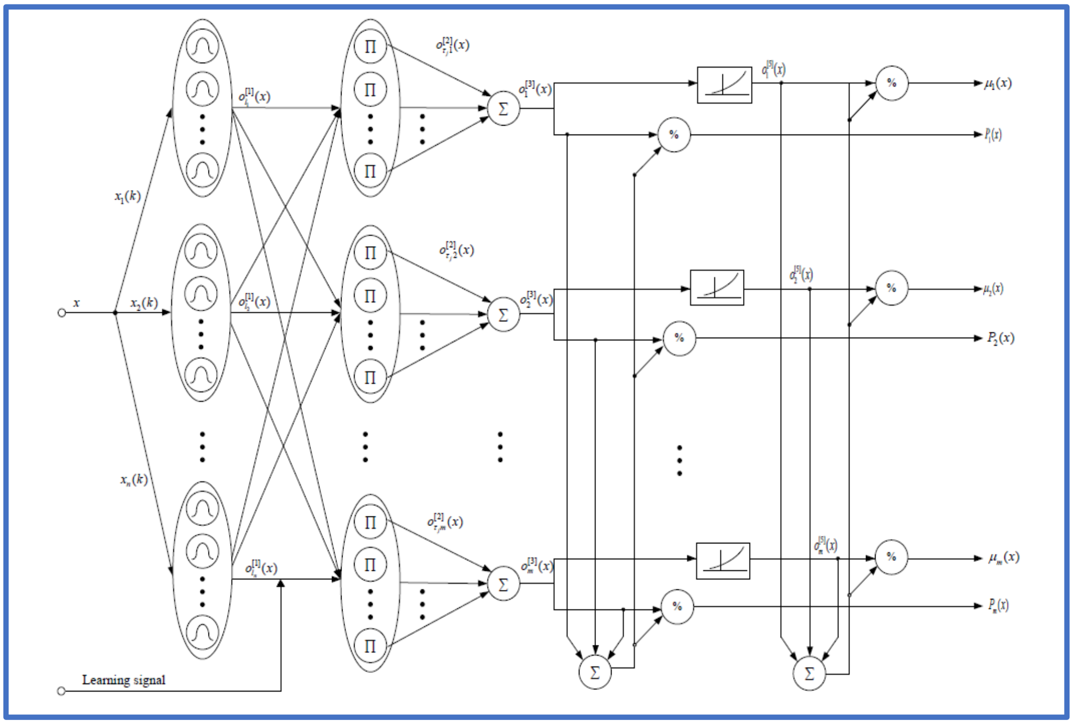

Figure 6. design of probabilistic neuro-fuzzy system

3.7. Fuzzy Logic Approximation and Deep Learning NN for Fish Concentration Maps

The application of ultrasound is one of the important and widespread applications 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, epigraphic 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).

3.8. 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).

3.9. Energy-efficient cluster-based unmanned aerial vehicle networks 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).

3.10. Evaluation Semantic segmentation of breast ultrasound image with fuzzy deep network

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.

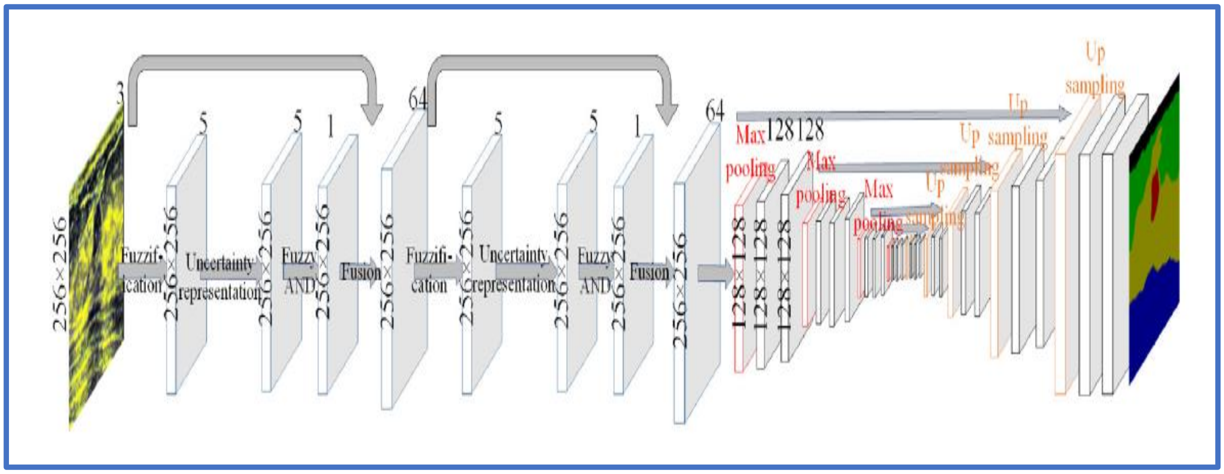

Figure 7. Structure of the proposed fuzzy FCN.

3.11. ECG-Based Driver's Stress Detection Using Deep Transfer Learning and FL 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.

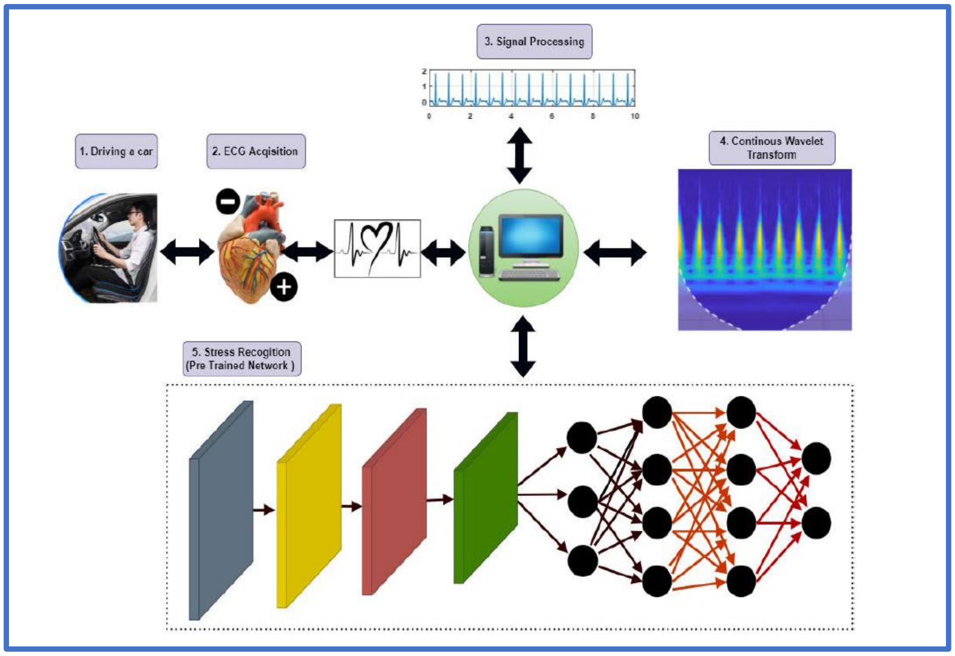

Figure 8. ECG-Based Driver's Stress Detection System architecture.

3.12. Crowd Emotion Prediction for Human-Vehicle Interaction

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).

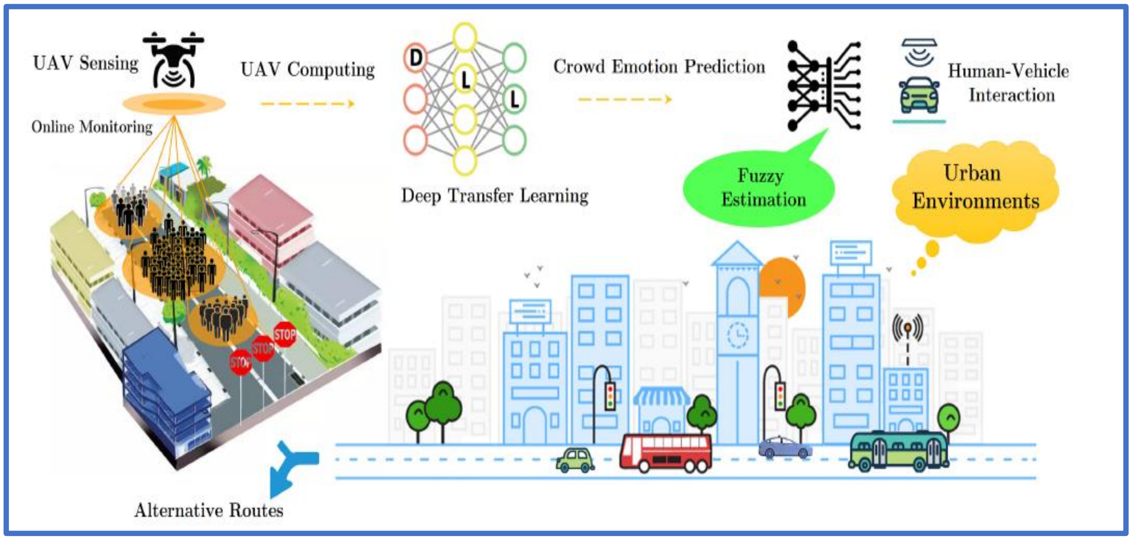

Figure 9. Fuzzy estimation, UAVs, and CAVs collaborate to determine the best pathway.

3.13. 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.

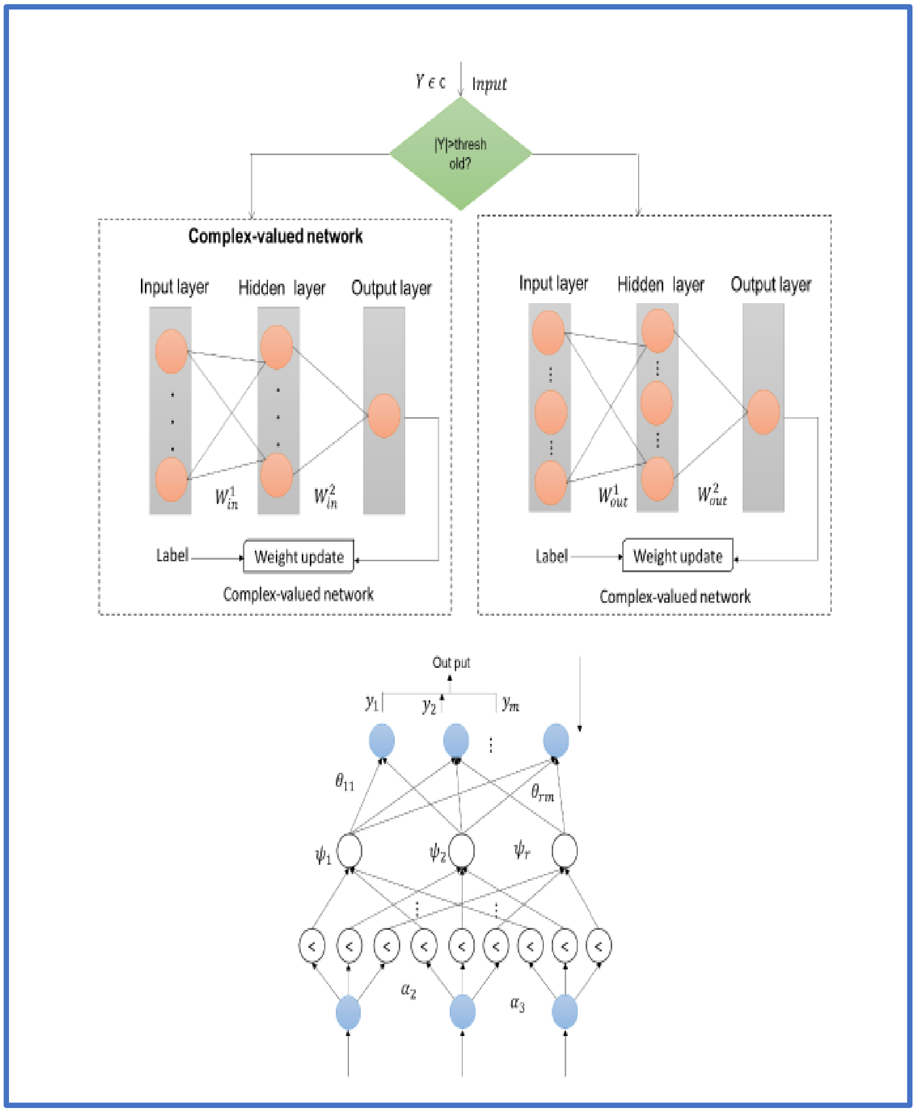

Figure 10. The AFL-DLE's architectural design.

3.14. 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.

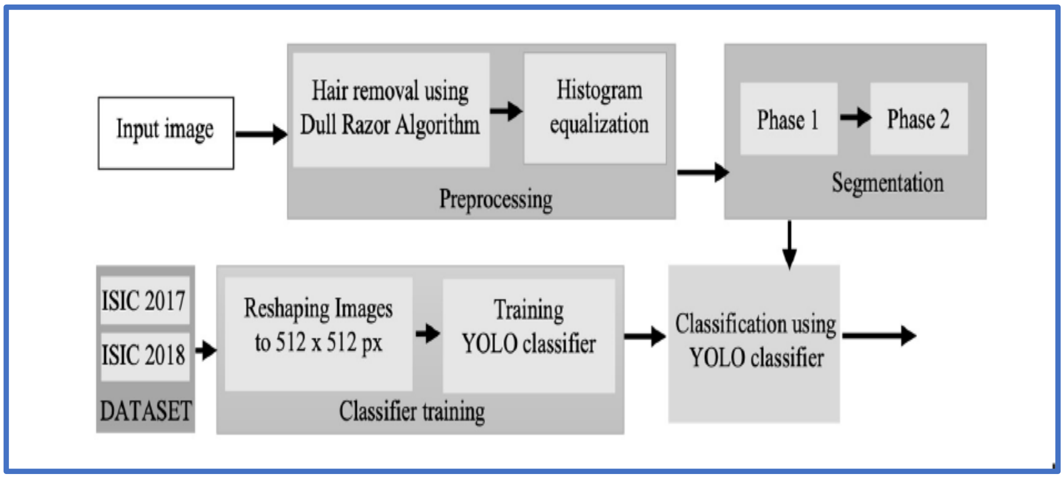

Figure 11. Flowchart of melanoma digital diagnosis.

3.15. 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).

4. Literature Survey Analysis

Table 1 summarizes various research projects and publications that focus on integrating fuzzy logic and deep learning techniques, particularly in the context of biometric systems. This literature review indicates a strong trend towards combining fuzzy logic with deep learning to enhance biometric systems, particularly in fingerprint and image classification tasks. The reported high accuracy rates, with several studies achieving above 99%, demonstrate the effectiveness of these combined methodologies. Using standard datasets like NIST-4, FVC2004, MNIST, and CIFAR-10 allows for benchmarking and comparison across different approaches. Moreover, exploring multimodal datasets, combining fingerprint and face data, highlights the potential for the fusion of different biometric modalities. The integration of technologies such as hybrid Mamdani fuzzy rules, convolutional neural networks, and the focus on interpretability indicate a comprehensive approach to developing robust and reliable biometric systems. Recent studies (2020-2022) continue to innovate, reflecting ongoing advancements and a promising future in this field.

The following summary of analysis:

1. **Trends in Research**

   Most studies focus on combining fuzzy logic with neural network techniques to enhance biometric systems, especially for fingerprint and image classification tasks. There is a notable emphasis on integrating these methodologies to improve accuracy and handle uncertainties inherent in biometric data.

2. **Accuracy**

   Several studies report high accuracy rates, with some achieving above 99%, indicating the potential effectiveness of combining fuzzy logic with deep learning. The highest reported accuracy is 99.58% using a TSK model for image classification (Yazdanbakhsh & Dick, 2019).

3. **Datasets:**

   Standard datasets like NIST-4, FVC2004, MNIST, and CIFAR-10 are common, allowing for benchmarking and comparison across different approaches. Multimodal datasets, combining fingerprint and face data, are also used to explore the fusion of different biometric modalities (Sharma & Singh, 2017).

4. **Technological Integration**

   Studies such as those involving hybrid Mamdani fuzzy rules and convolutional neural networks (Mohammed & Hussain, 2021) or the integration of fuzzy logic into CNNs (Sharma et al., 2019) highlight the diverse ways these technologies can be combined. The focus on interpretability (Xi & Panoutsos, 2018) indicates an interest in achieving high accuracy while also understanding and explaining the decision-making processes of these complex models.

5. Application Areas:

The primary application areas include fingerprint classification, image classification, and multimodal biometric systems, reflecting the broad applicability of these techniques in security and identification systems.

6. **Recent Developments:**

Recent studies (2020-2022) continue to explore novel integrations of fuzzy logic and deep learning, emphasizing ongoing interest and advancements in this field.

5. Conclusion

The fuzzy logic and deep learning techniques integrating in biometric systems, represents a significant advancement. It enhances the accuracy and reliability of image and fingerprint classification tasks. This literature review and analysis reveal a strong trend towards using these combined methodologies to address the inherent uncertainties in biometric data, achieving high accuracy rates, often exceeding 99%. The use of standard datasets like NIST-4, FVC2004, MNIST, and CIFAR-10 allows for meaningful benchmarking and comparison across various approaches, while the exploration of multimodal datasets underscores the potential for fusing different biometric modalities to improve authentication reliability. Technological integrations, such as hybrid Mamdani fuzzy rules with convolutional neural networks (CNNs) and the application of fuzzy logic within CNNs, demonstrate the diverse and robust ways in which these technologies can be combined. The ongoing advancements, as indicated by recent studies from 2020 to 2022, suggest a promising future in this field, with the potential to further improve biometric systems and extend these methodologies to other domains, such as healthcare diagnostics and energy management.

Future research should focus on expanding the application of fuzzy logic and deep learning integration beyond biometric systems to other critical areas, such as healthcare diagnostics, where accurate and reliable decision-making is paramount. Additionally, there is a need to explore the interpretability of these complex models further, ensuring that the decision-making processes are transparent and understandable to users. Developing new hybrid models incorporating the latest advancements in deep learning, such as transformer architectures, with fuzzy logic could lead to even higher accuracy rates and broader applicability. Moreover, exploring real-time processing capabilities and the scalability of these techniques will be essential for their implementation in large-scale systems.

Finally, future studies should consider the ethical implications of these technologies, particularly in sensitive areas like security and healthcare, to ensure that their deployment is practical and responsible.

Table 1: Summary of literature review (applications and methods)

Author	Application	Method	Accuracy	Dataset
(Mohamed & Nyongesa, 2002)	Automatic Fingerprint Classification System	Fuzzy Neural Techniques	98.5%	NIST-4
(Ezhilmaran & Adhiyaman, 2017)	Fingerprint matching and correlation checking	fuzzy logic level 2	--	NIST DB4 and FVC 2004
(Sharma & Singh, 2017)	Multimodal Biometric System Fusion Using Fingerprint and Face	Fuzzy Logic	99.5	FVC2002 + Face94
(Wang et al., 2016)	Damaged Fingerprint Classification	Deep Learning Convolution Neural Network (CNN).		FVC2004
(Mohammed & Hussain, 2021)	Analysis and Identification of Images	Hybrid Mamdani Fuzzy Rules and Convolutional Neural Networks	98٪	--
(Sharma et al., 2019)	Handwritten digits recognition and Image Classification	Fuzzy based Pooling in Convolutional Neural Network	94%	MNIST, CIFAR-10
(Popko, & Weinstein, 2016)	Handwritten Digits Recognition	Fuzzy Logic Module of Convolutional Neural Network	99%	--
(Xi & Panoutsos, 2018)	Classification Rules & linguistic interpretability	Convolutional Neural Networks with RBF Fuzzy Logic	96%	MNIST
(Subhashini et al., 2022)	Opinion/Sentiment analysis classification model	three-way decision-making fuzzy logic and a convolutional neural network	91.23% , 92.23%	Movie review, eBook review
(Das et al, 2020)	A Survey paper	Fuzzy Logic and Deep Neural Networks	-	-
(Yazdanbakhsh, & Dick, 2019)	Image classification	A Deep neuro-fuzzy network	99.58%, 88.18%	MNIST, CIFAR-10

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