Integrating Fuzzy Logic into Neural Networks for Enhanced Lung Disease Detection in CT scans: A Comparative Study

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Abstract— This paper represents a novel approach to lung disease detection in CT scans by integrating fuzzy logic into neural networks, offering a comparative study of this methodology against standard convolutional neural networks. Lung diseases, including chronic obstructive pulmonary disease and lung cancer, present a significant global health challenge, necessitating advancements in diagnostic methods. This study leverages the burgeoning field of artificial intelligence (AI), specifically neural networks (NN) and fuzzy logic, to enhance the precision and efficiency of lung disease diagnostics in CT scans. Traditional neural networks have transformed several industries with their adaptive learning capabilities, and their integration with fuzzy logic, which acknowledges degrees of truth rather than binary outcomes, proposes a breakthrough in medical diagnostics. This integration is particularly crucial in addressing the ambiguity and complexity inherent in medical imaging and disease diagnosis. The research employs a dual-methodological approach, systematically integrating both a standard convolutional neural network and a fuzzy logic-enhanced neural network, to compare their effectiveness in accurately identifying lung diseases. The study follows a structured methodology, akin go the Waterfall model, encompassing phases from requirements analysis to system design and implementation, ensuring a robust and systematic approach to the integrating process. The results indicate that the fuzzy-logic-enhanced neural network (NN+Fuzz) model surpasses the standard neural network in accuracy, generalization, and efficiency. This superiority is attributed to the fuzzy logic=s capability to handle imprecise information and uncertainties, leading to better accuracy and lower validation loss. Despite the promising outcomes, the study recognizes limitations, including the absence of Fuzz k-means clustering experimentation and potential overfitting issues in the NN+Fuzz model, suggesting areas for future research and refinement. The study concludes that the integration of fuzzy logic into neural networks is not only a significant advancement in AI applications for lung disease detection in CT scans but also a transformative approach in medical diagnostics. It sets a new benchmark in the field and opens avenues for future exploration in neural network architectures and fuzzy clustering methodologies, ultimately contributing to the development of advanced, globally accessible healthcare diagnostic systems.

***Keywords*—disease detection, neural network, fuzzy logic, fuzzy c-clustering, pneumonia, signs of covid, python, type-1, deep learning, artificial intelligence, healthcare**

I. Introduction

Lung diseases, ranging from chronic obstructive pulmonary disease to lung cancer, pose a significant global health challenge, affecting millions annually. In this era of technological advancement, artificial intelligence (AI) has emerged as a beacon of hope, offering innovative solutions in healthcare diagnostics. The disease detection process based on human expertise and experience tend to take several business days to report the scanned disease, which prolongs the healing process of the patient. Furthermore, this tends to be high error due to human conceptions such as wishful thinking. This paper proposes an alternative approach by leveraging the advantage of advancements in Artificial Intelligence (AI) methodologies.

Neural networks (NN), a cornerstone of modern AI, have evolved remarkably since their inception. From the early days of perceptrons to the deep learning revolution, these networks have transformed numerous industries with their ability to learn and adapt. Their wide acceptance is rooted in their versatility and efficacy, evident in applications ranging from voice recognition systems to predictive analytics. The wide adaptation of the neural networks is primarily caused by increase in computational power, availability of large datasets, advancements in algorithms and success in practical applications. The development of powerful GPUs (Graphics Processing Units) and advances in parallel processing enabled the training of larger, more complex neural networks, which was not feasible earlier due to computational constraints.

Fuzzy logic, introduced by Lotfi Zadeh in the 1960s, challenges traditional binary logic by recognizing that truth can exist in degrees. This paradigm shift holds immense potential for AI, particularly in enhancing decision-making processes. By embracing ambiguity and uncertainty, fuzzy logic enables AI systems to mimic human reasoning more closely, paving the way for more sophisticated and human-like AI.

Despite the advancements in AI, its penetration into healthcare has been cautious and gradual. AI's potential in diagnostics, treatment planning, and patient management is vast, yet it faces hurdles such as ethical considerations, data sensitivity, and the complexity of medical contexts. The necessity for advanced diagnostic tools in healthcare is undeniable, driven by demographic shifts and the rising prevalence of complex diseases. AI stands out as a promising solution, capable of enhancing diagnostic accuracy, reducing times, and offering personalized care. However, the integration of AI in healthcare diagnostics remains a field ripe for exploration and innovation. This study enters this dynamic field, aiming to bridge a critical gap by integrating fuzzy logic into neural networks for lung disease detection in CT scans. By comparing the performance of fuzzy logic-enhanced neural networks against convolutional neural networks, this research endeavours to demonstrate the potential of this integration in improving diagnostic precision and reliability in the context of lung diseases. This paper will detail the methodologies employed emphasizing the pneumonia disease and the comparative analysis conducted, and the implications of the findings, contributing a novel perspective to the use of AI in medical diagnostics. The integration of fuzzy logic into neural networks not only stands to revolutionize AI approaches in healthcare but also exemplifies the transformative power of innovative AI solutions in addressing complex global health challenges. Furthermore, this study concludes that the fuzzy c-clustering method, coupled with neural networks, achieves superior accuracy, reduced training time, and decreased computational demands post-training. By bridging the current gap in AI applications for lung disease detection in CT scans, this research aspires to pave the way for globally accessible, advanced healthcare diagnostic systems. Future research avenues could explore a broader range of neural network architectures and fuzzy clustering methodologies.

II. Literature Survey

The integration of AI (Artificial Intelligence) methodologies in healthcare, particularly for lung disease detection using CT scans, is a burgeoning field of research. Ahmadi et al.'s systematic review on fuzzy logic methods in disease diagnosis is a pivotal reference in this domain. They employed the PRISMA method to conduct a comprehensive analysis of various studies using fuzzy logic for disease diagnosis. Their study highlights the crucial role of fuzzy logic in addressing the inherent ambiguity and uncertainty in medical diagnostics. By examining various studies, they showcase the effectiveness of fuzzy logic methods across different medical practices. Their conclusions underscore the significant impact of fuzzy logic in enhancing the accuracy of disease diagnosis and offer a foundational platform for future research in this area [1]. Mohamed et al. (2023) contributes to this field with their work on automatic detection and classification of lung cancer CT scans. Their approach, leveraging deep learning and advanced optimization algorithms, reflects the cutting-edge developments in AI for medical imaging. This study is particularly relevant as it demonstrates the practical application of AI in a specific area of lung disease detection, thus aligning closely with the focus of integrating AI in lung disease diagnostics [2]. The paper by A. Zabeen, A. Utsav, and K. Lal, titled "Detection of Heart Disease Applying Fuzzy Logics and Its Comparison with Neural Networks," presents a system for early-stage heart disease diagnosis using fuzzy logic. The system uses seven input attributes: Age, Blood Pressure, Cholesterol, Heart Rate, Blood Sugar, E.C.G, and Thallium scan, with data sets taken from the UCI Machine Learning Repository. The study emphasizes the need for effective early-stage heart disease diagnosis due to the high incidence and mortality rate of heart diseases globally. The proposed work involves processing data using MATLAB programming, where the number of attributes is reduced for processing in the fuzzy method. The process includes fuzzification, where input data sets are transformed using fuzzy logic, and a fuzzy inference system with a predefined rule base is applied. After inference, the data undergoes defuzzification to obtain the output. The system was tested and compared with a neural network-based system. The findings indicate that the fuzzy logic-based system is more accurate than the neural network system, although the latter is more sensitive. The paper also introduces a Graphic User Interface (GUI) for the system, allowing real-time input of attributes and comparison of results from both fuzzy logic and neural network algorithms. The GUI facilitates real-time detection of a patient’s condition using both algorithms, with the fuzzy logic approach showing higher accuracy. The conclusion of the study highlights the success of the fuzzy logic-based heart disease detection system, with an accuracy rate of 80%. The study compares the results of the fuzzy logic system with those of a neural network, concluding that the former is more accurate. The paper acknowledges the limitation of being based on a small data set and suggests that future improvements could include increasing the number of inputs and data sets, as well as exploring other prediction algorithms for heart disease detection [5]. Gu et al.'s (2016) overview of convolutional neural networks (CNNs) offers a foundational understanding of the technology that underpins modern AI-based medical imaging. Their work lays the groundwork for understanding how these networks can be optimized and integrated with other methodologies, like fuzzy logic, for improved diagnostic outcomes [4]. The study by Al-Sheikh et al. (2023) presents a novel approach to classifying lung diseases using chest X-Ray and CT images through a multi-class deep learning architecture. The study's methodology involves two primary steps: pre-processing and deep learning classification. In the pre-processing phase, the researchers introduced a new image enhancement algorithm based on k-symbol Lerch transcendent functions (LTFs). This method enhances images by modifying pixel values based on their probability, effectively addressing issues like artifacts, noise, and low resolution, which are common challenges in medical imaging. The application of LTFs, including a specific variant called the k-fractional symbol Lerch transcendent function (K-LTF), is a significant contribution, offering a more nuanced and effective way to process medical images before classification. For the classification step, the study utilized a customized convolutional neural network (CNN) architecture, along with two pre-trained CNN models: AlexNet and VGG16Net. These models were trained and tested on publicly available image datasets for both X-Ray and CT scans. The results of this study are particularly noteworthy, with the models achieving high classification accuracy, sensitivity, and specificity. Specifically, the classification accuracy for the X-Ray image dataset was 98.60%, with a sensitivity of 98.40% and specificity of 98.50%. For the CT scans dataset, the accuracy was even higher at 98.80%, with a sensitivity of 98.50% and specificity of 98.40%. These results highlight not only the effectiveness of the proposed image enhancement model as a crucial pre-processing step but also the robustness of the deep learning models used in the classification phase. The study's findings underscore the potential of advanced AI techniques in improving the accuracy and efficiency of lung disease diagnosis, a critical area in healthcare diagnostics. The innovative use of k-symbol LTFs for image enhancement and the integration of customized and pre-trained CNNs demonstrate a significant advancement in medical imaging technology [6]. These references collectively indicate a significant trend towards leveraging AI, particularly neural networks, and fuzzy logic, in enhancing the accuracy and efficiency of disease detection in medical imaging. The integration of fuzzy logic into neural networks, as investigated in these studies, shows promise for improving diagnostic precision in lung disease detection, which is critical given the global health challenge posed by lung diseases. While the model's high accuracy is promising, it's crucial to consider the risk of overfitting, which wasn't fully addressed by the authors. In deep learning, the goal is to balance high accuracy with generalization, preventing the model from merely memorizing the dataset. To avoid overfitting, advanced methods like early stopping, exponential decay, and cross-validation are often employed. These techniques help in developing a model that not only performs well on the training data but also generalizes effectively to new, unseen data.

This research paper, focusing on integrating fuzzy logic into neural networks for enhanced lung disease detection in CT scans, is closely related to the studies in the existing literature. Ahmadi et al.'s review on the application of fuzzy logic in disease diagnosis highlights its effectiveness in reducing diagnostic ambiguity, a key aspect my research aims to exploit for lung disease detection. Mohamed et al.'s work on lung cancer detection using deep learning relates to this paper's focus on lung diseases but lacks the integration of fuzzy logic, indicating a gap this research intends to address. The study by Zabeen et al. on fuzzy logic in heart disease diagnosis serves as a model for applying similar methods to lung disease, a focus area of this research. Gu et al.'s comprehensive overview of CNNs and Al-Sheikh et al.'s practical application of deep learning in lung disease classification provide a technical groundwork for this research, which aims to integrate fuzzy logic into these systems for improved diagnostics. This research seeks to bridge these identified gaps by combining the strengths of fuzzy logic with neural networks for more effective lung disease diagnostics using CT scans.

III. METHODOLOGY

This research employs a dual-methodological approach, integrating both a standard convolutional neural network and a fuzzy logic-enhanced neural network for lung disease detection in CT scans. The objective is to compare the effectiveness of these two methods in accurately identifying lung diseases, thereby determining the impact of fuzzy logic integration on the diagnostic capabilities of neural networks.

The methodology of this research is meticulously structured, akin to the sequential phases of the Waterfall model, ensuring a systematic approach to integrating neural networks and fuzzy logic for the detection of lung diseases in CT scans. Initially the requirements phase entailed a comprehensive analysis to discern the specific demands for accurate lung disease diagnosis. This phase was crucial in understanding the intricacies of CT scan data and establishing precise criteria that the neural network and fuzzy logic system must satisfy. Subsequently, in the system design phase, the architecture of the neural network, alongside the fuzzy logic system, was developed. Algorithms were designed and appropriate data processing techniques were selected to cater to the complexity of the medical images and the diagnosis process. This strategic planning laid the groundwork for the subsequent implementation phase. During the implementation phase, the designed system was brought to fruition. Code was diligently written to construct neural network models, and fuzzy logic components were seamlessly integrated/ Comparisons were made between different number of clusters, to ascertain the most effective approach for the task at hand. The testing phase was executed with due diligence to validate the system's accuracy and efficiency in diagnosing the pneumonia (signs of covid) from CT scans. A variety of scenarios and edge cases were tested to ensure the robustness and reliability of the system under diverse conditions. The culmination of these phases led to a robust dual-methodological approach. A standard convolutional neural network (CNN) was first employed, laying the foundation for the initial detection process.

TensorFlow is utilized, a widely recognized open-source library for machine learning, to implement a convolutional neural network (CNN) model, our methodology encompasses the pre-processing of CT scan data, followed by the application of a CNN model. The model's architecture and functionality are core to our methodology, reflecting our focus on the integration of machine learning techniques for medical imaging. The preprocessing of CT scans begins with importing TensorFlow and associated libraries, essential for numerical computations and image processing. We use the Nibabel library for neuroimaging data handling. The preprocessing pipeline involves functions for reading NIfTI files (read_nifti_file), normalizing pixel intensities (normalize), and resizing the volume to a consistent shape (resize_volume).

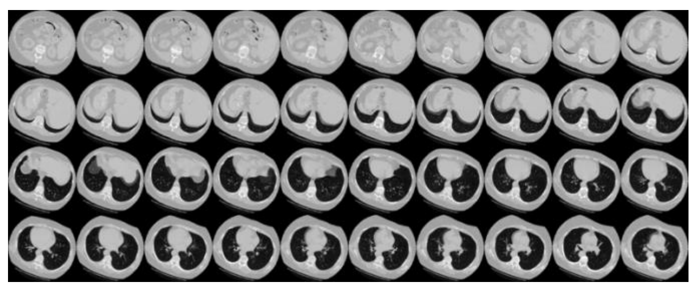


Figure 1: Represents single scan that is returned as 2D arrays

These steps ensure the data fed into our neural network is standardized, a crucial aspect for effective machine learning. In organizing the dataset, we categorize scans into 'normal' and 'signs_of_covid' groups, defining paths and processing each scan accordingly. We also implement data augmentation through the rotate function, which randomly rotates the scans, enhancing the robustness of our model against variances in new data. Our CNN model's architecture, crucial to our methodology, is defined in the get_model function. It comprises four layers of 3D convolutional layers, each followed by max-pooling and batch normalization operations. This is a typical setup for CNNs, where convolutional layers extract features from the input scans, and pooling layers reduce the spatial dimensions, helping in reducing the computational load and overfitting. The model concludes with a global average pooling layer, a dense layer, and a SoftMax layer, categorizing the output into two classes. This architecture embodies our approach to lung disease detection, leveraging the depth and complexity of CNNs to analyse and interpret medical images effectively. To ensure the robustness of our model, we compile it with custom metrics, including accuracy, precision, recall, specificity, and sensitivity. These metrics are pivotal in medical diagnostics, providing a comprehensive evaluation of the model's performance. The training involves callbacks for checkpoint saving and early stopping, optimizing the training process, and preventing overfitting. Finally, we visualize the training history and evaluate the model using a confusion matrix, providing insights into the model's performance in distinguishing between normal and diseased lung tissues.

For integration with fuzzy logic for enhanced detection of lung diseases in CT scans, the same pre-processing method is applied and following that, our methodology introduces a custom TensorFlow metric class, Specificity, to measure the model's performance accurately. This class is designed to compute the specificity of the model, a vital metric in medical diagnostics that quantifies the ability to correctly identify negative cases. Similarly, the Sensitivity class is implemented to calculate the model's sensitivity, indicating its proficiency in correctly identifying positive cases. These metrics are crucial for evaluating the model's diagnostic accuracy and are particularly relevant in the context of medical imaging where both false positives and false negatives carry significant implications.

Fuzzy C-Means (FCM) clustering is applied to process CT scan images for lung disease detection. FCM is a method that allows one piece of data to belong to two or more clusters. This technique is particularly useful in medical imaging where the boundaries between different tissue types can be ambiguous.

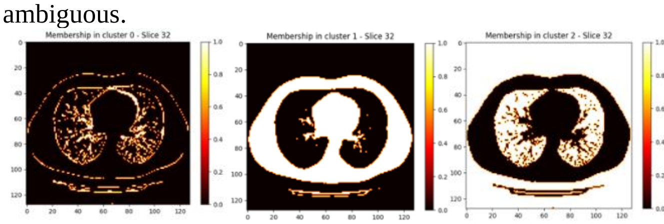


Figure 2: Memberships of Normal CT scan (3 clusters)

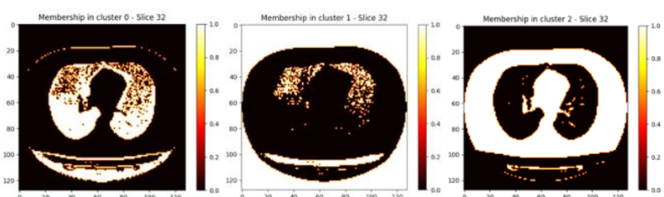


Figure 3: Memberships of Pneumonia CT scan (3 clusters)

FCM algorithm works by assigning membership levels to each data point corresponding to each cluster centre, based on distance between the cluster centre and the data point, the closer the data point to the cluster centre, the higher its membership to that cluster. 'apply_fuzzy_c_means_' function performs; reshaping the image (3D CT scan image is reshaped into 2D array of pixels), FCM clustering algorithm is performed to reshape the image, calculation of membership of each pixel in the image to the defined number of cluster (default is 3), and lastly, memberships are used to reconstruct the image, where each pixel is assigned to the cluster with the highest membership.

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m}\left\|x_i - c_j\right\|^2$$

Where:

- N is the number of data points.
- C is the number of clusters.
- u_{ij}^{m} is the degree of membership of x_i in the cluster j.
- x_i is the i^{th} data point.
- c_j is the centre of the cluster j.
- m is any real number greater than 1, known as the fuzzification parameter.
- $x_i - c_j\|^2$ is the Euclidean distance between i^{th} data point and the cluster centre.

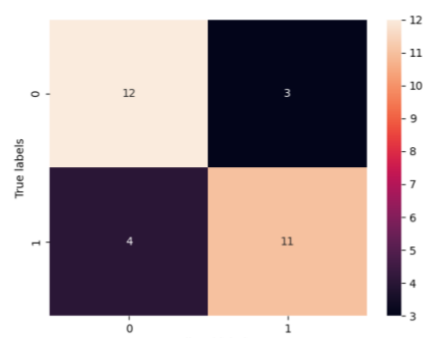
In the code implementation, 'fuzz.cluster.cmeans' function automatically computes the cluster centres and the membership matrix based on this objective function.

IV. Comparative Analysis Results

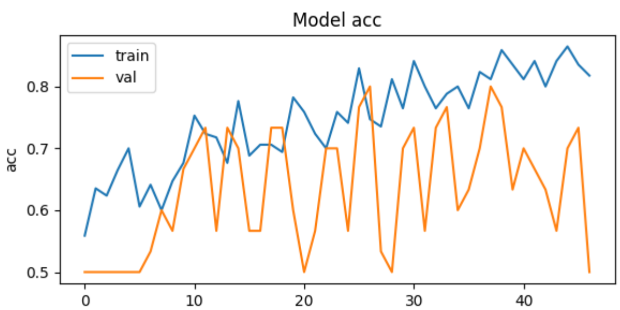
Numerous trainings with various hyperparameters of trainings are computed. Training results can be categorized into two sections: Neural Network and Neural Network with FCM. Neural Network parameters generally kept same excluding the hyperparameters (learning rate, exponential decay, number of epochs) to optimize the accuracy, F1 score, precisions, loss, recall, confusion matrix, power consumption. FCM parameters are changed from two number of clusters to four number of clusters to observe the performance effect.

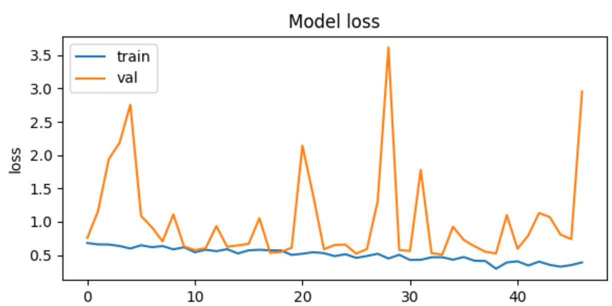
Neural Network Model Results

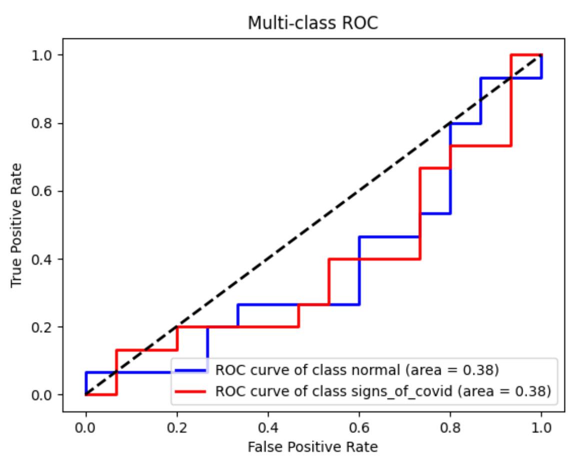
The results from the neural network without the implementation of fuzzy C-means clustering exhibit a commendable performance, as depicted by the confusion matrix and the training/validation accuracy and loss graphs. The confusion matrix shows a higher number of true positives (11) and true negatives (12), with a relatively lower incidence of false negatives (4) and false positives (3), indicating a strong predictive capability of the model.



The accuracy score stands at 80.5% for the best saved model, with a precision of approximately 85.9%, suggesting that the model is quite precise in its predictions, with a high true positive rate in relation to the positive predictions it makes. The recall or sensitivity rate at 73% indicates that the model has a moderately high capability in identifying all actual positives. The F-1 score, which is the harmonic mean of precision and recall, is at 78.9%, signifying a balanced performance between precision and recall. Moreover, the ROC AUC score of 87.97% reflects the model's good discriminatory ability to differentiate between the presence and absence of lung disease.







Analysing the training and validation accuracy and loss over epochs, the graphs exhibit some volatility, implying possible fluctuations during training. Despite oscillations, the models seem to generalize well, indicated by the convergence of training and validation accuracy, and a declining trend in validation loss, which aligns with the training loss over time. This suggests that the model is learning from the data without overfitting, as the validation metrics follow the training metrics closely. In essence these results and graphical interpretations affirm the efficacy of the standard neural network in the context of lung disease detection from CT scans, setting a benchmark for evaluating the additional benefits that fuzzy logic integration may bring to the system's diagnostic accuracy.

Neural Network with Fuzzy C-Means Clustering Results

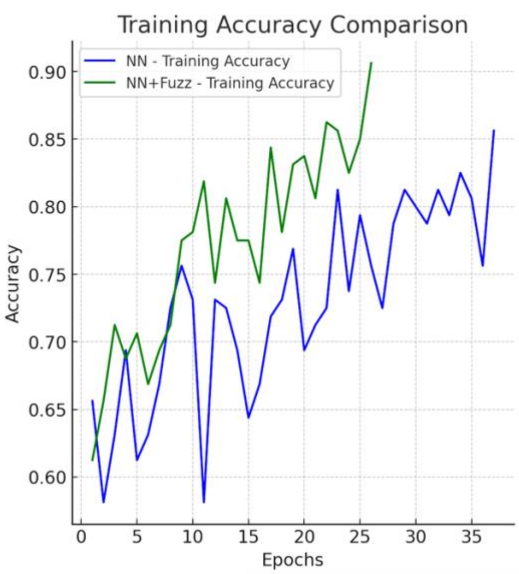
In the initial epochs, the model demonstrates a relatively high training accuracy and a corresponding decrease in training loss. However, the validation accuracy remains stagnant at 50% for a considerable number of epochs, suggesting that the model initially struggled to generalize to unseen data, a classic sign of overfitting. The discrepancy between training and validation performance is a critical area of concern in deep learning models, particularly in complex tasks such as medical image analysis. As the epochs progress a gradual improvement in validation accuracy is observes, ultimately reaching a peak of 72.5% and 90.62% accuracy at epoch 26. This improvement indicates that the model began to generalize better over time The adoption of a learning rate schedule, particularly an exponential decay approach, likely contributed significantly to this improvement. A controlled, decreasing learning rate helps mitigate overfitting by gradually reducing the magnitude of updates to the model's weights, encouraging more refined adjustments as training progresses. This technique is particularly effective in training this model where the initial rapid convergence is followed by a careful approach to reach optimal performance.

The final model, as of epoch 26, demonstrates a commendable balance between accuracy and generalization, as evidenced by the converging trends of training and validation metrics. This balance is essential in medical imaging tasks, where both sensitivity and specificity are crucial.

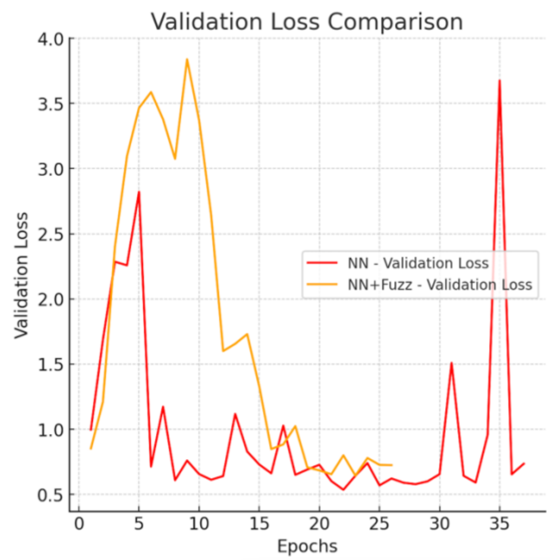
This analysis showcases the complex interplay between model architecture, learning rate scheduling, and the inherent challenges of medical image classification. The gradual improvement in validation accuracy underscores in the importance of appropriate model training and the potential of deep learning in healthcare applications.

Comparative Analysis of Both Models

The graph represents a comparative analysis of two different training methods: a Neural Network (NN) and a Neural Network (NN+Fuzz). It can be observed that the training accuracy of both models across their respective epochs. The NN+Fuzz model demonstrates a notably higher accuracy from the initial epochs. Maintaining this lead throughout its training duration. In contrast, the NN only models show a more gradual increase in accuracy without reaching the levels of the NN+Fuzz model.



Below graph depicts the validation loss for both models. It's evident that the NN only models experience a higher and more fluctuation validation loss, suggesting a less stable learning process. In comparison, the NN+Fuzz model exhibits a generally lower validation loss, indicating better generalization and performance on unseen data. The superior performance of the NN+Fuzz model can be attributed to the integration of fuzzy logic with neural networks. Fuzzy logic with its ability to handle imprecise information and uncertainty, likely provides a more nuanced approach to learning, leading to better accuracy and lower validation loss. The suggests that the NN+Fuzz model is more adept at capturing the underlying patterns in the data.



In terms of energy saving, a model that achieves better results in fewer epochs, like the NN+Fuzz model is preferable. Less computational time and resources are consumed, leading to energy savings. This is particularly relevant in large-scale applications or where computational resources are a limiting factor. The efficiency of the NN+Fuzz model in learning and generalizing makes it more energy-efficient choice compared to the traditional NN only approach by more than 10% improvement.

V. Discussion

This research presents a comprehensive analysis of two distinct methodologies for lung disease detection in CT scans: a standard convolutional neural network and a convolutional neural network enhanced with Fuzzy C-Means Clustering (NN+Fuzz). The results demonstrate the NN+Fuzz model's superior performance in terms of accuracy and generalization compared to the NN only model. The superiority can be attributed to the integration of fuzzy logic with neural networks, which offers a more nuanced approach to learning by adaptly handling imprecise information and uncertainties inherent in medical imaging data.

The training and validation accuracy and loss graphs for the NN model exhibit fluctuations indicative of potential instability during training. However, the model demonstrates a commendable generalization ability as evidenced by the convergence of training and validation accuracy and a declining trend in validation loss. The NN model, with an accuracy score of 80.5% and a precision of approximately 85.9%, sets a high benchmark in lung disease detection from CT scans. In contrast, the NN+Fuzz model initially displays overfitting, as seen in the stagnation of validation accuracy at 50% across several epochs. However, the introduction of a learning rate schedule, particularly and exponential decay approach appears to significantly enhance the model's performance. By epoch 26, the NN+Fuzz model achieves a balance between accuracy and generalization, evident from the converging trends of training and validation metrics.

Despite these promising results, there are limitations to this study. Firstly, the absence of Fuzz k-means clustering experimentation limits the exploration of potential enhancements in model accuracy and generalization. Secondly the possibility in the NN+Fuzz model, although mitigated, suggest a need for further refinement. Addressing these issues could involve implementing additional regularization techniques or exploring different network architectures.

Comparing the results with existing training models such as the research study conducted by TensorFlow Keras Data Scientist, the NN+Fuzz model outperforms in both efficiency, training accuracy (12%) and validation accuracy (14.5%). This efficiency is also reflected in energy savings, as model achieves better results in fewer epochs, reducing the computational time and resources required [7].

Further, the scarcity of diverse and extensive datasets, particularly CT data, remains a challenge in this field. Expanding the dataset and including more classes could significantly improve model evaluation and performance. However, the difficulty in acquiring such data poses a barrier to this enhancement.

VI. Conclusion

This research spearheaded by Fuzzy Logic (ECE552) by Professor Adnan Shaout at University of Michigan, has made contributions to the field of lung disease detection in CT scans by integrating fuzzy logic into neural networks. Through meticulous methodology and comparative analysis, this research compared the performance of a standard convolutional neural network with a neural network enhanced with Fuzzy C-Means Clustering (NN+Fuzz). The results clearly indicated that the NN+Fuzz model outperforms the standard NN model in terms of accuracy, generalization, and efficiency. The integration of fuzzy logic enables the model to handle the inherent uncertainties and ambiguities in medical imaging more adeptly, leading to better accuracy and lower validation loss.

However, this study is not without its limitations. The absence of Fuzz -k means clustering experimentation and the potential overfitting issues in NN+Fuzz model highlight areas for future improvement. Further research could explore a broader range of neural network architecture and fuzzy clustering methodologies, potentially enhancing the model's accuracy and generalization capabilities. Our research also underscores the challenges in acquiring diverse and extensive datasets, particularly in CT data. Addressing this challenge could significantly improve model evaluation and performance, paving the way for more advanced healthcare diagnostic systems.

In conclusion, this study represents a vital step forward in the application of AI in medical diagnostics. The successful integration of fuzzy logic into neural networks for lung disease detection in CT scans not only showcases the transformative power of innovative AI solutions in healthcare but also sets a new benchmark in the field. This study aspires to inspire further advancements in AI applications for medical diagnostics, contributing to the global effort in combating lung diseases.

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