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HIGH-DIMENSIONAL DATA-DRIVEN PNEUMONIA DIAGNOSIS USING ANFIS

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ABSTRACT

The present research paper presents a transformative diagnostic framework for pneumonia employing an Adaptive Neuro-Fuzzy Inference System tailored particularly for clinical high-dimensional data. The ANFIS device combines the exclusive qualities of fuzzy logic and the flexible nature of neural networks. It can analyze complicated patient data. Our extensive evaluation across multiple clinical datasets demonstrates the unmatched accuracy rate of diagnosis, which exceeds 95 percent, an accuracy rate exceeding 90%, and a similar sound recall rate, resulting at an F1 score of 0.92. A ROC-AUC of 0.98 indicates that our model, with an excellent ability to differentiate pneumonia presentations from a healthy, nuanced situation. This is a game changer for clinical diagnostics industries and suggests the system's implications for pneumonia detection with high accuracy. This integration of neuro-fuzzy systems with machine learning opens new avenues for the development of high-accuracy diagnostic tools, potentially revolutionizing the domain of medical diagnostics and patient care.

Keywords: Adaptive Learning, Clinical Data Analysis, Diagnostic Accuracy, Fuzzy Logic, High-Dimensional Data, Neuro-Fuzzy Systems, Pneumonia Diagnosis, ROC-AUC.

1. INTRODUCTION

Pneumonia, an acute respiratory infection affecting the lungs, is a major cause of mortality and morbidity worldwide. It can be caused by a variety of pathogens, including bacteria, viruses, and fungi, and can range in severity from mild to life-threatening. Symptoms typically include cough, fever, and difficulty breathing, which vary depending on the causative agent and the patient's overall health. Vulnerable populations such as the elderly, children, and individuals with pre-existing health conditions are particularly at risk. The complexity of pneumonia's etiology and symptomatology poses significant challenges in its diagnosis and management, making it a focal point of medical research and public health initiatives.

Current Diagnostic Methods and Limitations: The diagnosis of pneumonia primarily relies on clinical assessment, radiological imaging, and microbiological testing. Chest radiographs, while commonly used, can sometimes fail to detect pneumonia, or differentiate it from other respiratory conditions. Microbiological tests, including sputum culture and blood tests, can provide specific information about the causative agent but are time-consuming and may not always yield conclusive results. These limitations often lead to delayed diagnosis and treatment, contributing to increased risk of complications, especially in resource-limited

settings where advanced diagnostic tools are not readily available.

2. LITERATURE REVIEW

Improved pneumonia identification has improved the results for patients in recent years.

In "The Journal of Respiratory Medicine" (2021), Johnson et al [1]. showed that High-Resolution Computed Tomography (HRCT) can diagnose pneumonia. HRCT may detect lung abnormalities associated with pneumonia more accurately than traditional X-rays, especially in viral pneumonia, which proved essential during the COVID-19 pandemic.

Smith and colleagues (2022) [2] in "Clinical Infectious Diseases," stressed molecular diagnostic tools. Polymerase Chain Reaction (PCR) testing might quickly and reliably detect bacterial and viral infections, enabling more targeted and effective therapies. AI in pneumonia diagnostics is a major advance.

Lee et al. (2023) [3], published in "The Lancet Digital Health," showed how AI systems trained on hundreds of chest X-ray pictures may detect pneumonia earlier than traditional methods. This is a promise for resource-constrained areas with limited access to modern imaging techniques.

In "The American Journal of Medicine" (2022), Gupta and colleagues [4] stressed the relevance of point-of-care ultrasonography (POCUS) in detecting pneumonia, especially in children. In emergency situations, POCUS can diagnose pneumonia quickly, accurately, and non-invasively, enabling immediate treatment decisions.

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3. RELATED WORK

This research [5] introduces a technique for diagnosing childhood pneumonia by analyzing cough noises. The system combines manually designed features and deep learning embeddings within a multilayer perceptron. The methodology is remarkable for its ability to detect pneumonia using cough sounds accurately and precisely, without the need for invasive methods. Nevertheless, the model's generalizability across varied demographics and circumstances may be constrained due to its dependence on a particular dataset consisting of just 491 cough sounds.

The paper [6] presents a novel method for automatically analyzing cough sounds to identify pneumonia in children. This method incorporates cough sound denoising, segmentation, and classification using neural networks. This approach demonstrates promise for efficient and cost-effective diagnostic procedures. The primary constraint lies in its reliance on the diversity and magnitude of the dataset, potentially impacting its suitability in diverse real-world situations.

This research [7] investigates the application of a deep neural network for the purpose of denoising cough sound recordings. The COUGHVID dataset is utilized for this purpose. The methodology enhances the quality of cough sounds and surpasses conventional denoising methods, which is advantageous for the diagnosis of respiratory illnesses such as COVID-19. Nevertheless, the study is limited by the quantity of the dataset and specifically examines only one form of noise at a constant signal-to-noise ratio, which may restrict its wider relevance. This study [8] presents an advanced algorithm that is capable of automatically screening for COVID-19 utilizing cough sounds collected from a mobile application. The technique utilizes a Convolutional Neural Network (CNN) methodology. The system's accuracy is excellent, but its usefulness depends on the dataset's comprehensiveness and lacks thorough validation across varied patient demographics and environmental situations, which are crucial for real-world applications.

Author	Methodology	Key Findings	Limitation
R. V. Sharan et al. [9]	Automated Cough Sound Analysis (ACSA)	Effectiveness of cough sound analysis	Dataset and specifics not provided
J. Jyostna and M. Santhoshi [10]	Advanced Deep Learning Techniques (ADLT)	Efficacy of deep learning models	Limited by depth of learning models
R. G. Poola et al. [11]	Utilizing Squeeze Net and Feature Extraction algorithm in Deep Learning (FEDL)	Advantages of Squeeze Net application	Requires further validation
W. Liu et al.[12]	Attention-Guided Partial Domain Adaptation in Automated Diagnosis from Chest X-Ray Images (ADXRay)	Benefits of domain adaptation	Specificity of domain adaptation

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4. PROPOSED ALGORITHM

The algorithm for Adaptive Neuro-Fuzzy Inference System (ANFIS) is given as follows. Clinical data are input, and a pneumonia diagnostic probability is generated. Before training an ANFIS model on the training data, Gaussian membership functions for each input are defined to calculate rule strength. Normalising these strengths determines how much each rule applies. To minimise the difference between expected and actual outputs, the ANFIS network is initialised with predefined rules and updated using gradient descent for each training session. The system generates a weighted total of rule outputs and becomes a trained diagnostic tool after enough training epochs. This method uses neural networks and fuzzy logic to approximate non-linear functions and handle input data ambiguity, which is typical of clinical diagnosis.

Algorithm: *Algorithm 1 ANFIS-Based Pneumonia Diagnosis*

1: Input: *Patient clinical data*
2: Output: *Pneumonia diagnosis probability*
3: procedure *TrainANFISModel (Training Data)*
4: Define Gaussian membership functions for each input x_i : $\mu_{A_i}(x_i) = \exp(-\frac{(x_i - c_i)^2}{2\sigma_i^2})$
5: Calculate the firing strength of a rule : $w_i = \prod_{j=1}^{n} \mu_{A_{ij}}(x_{ij})$
6: Normalize the firing strengths: $\overline{w_i} = \frac{w_i}{\sum_{k=1}^{N} w_k}$
7: Initialize ANFIS network with predefined rules
8: ***for*** *each epoch* ***do***
9: Update the rule parameters using gradient descent: $\theta_{new} = \theta_{old} - \eta \nabla E(\theta_{old})$
10: Compute the overall output as a weighted sum of the rule outputs $O = \sum_{i=1}^{N} \overline{w_i} f_i(x)$
11: ***end for***
12: ***return*** *Trained ANFIS Model*

The flowchart outlining the process flow of an ANFIS (Adaptive Neuro-Fuzzy Inference System) model used for the diagnosis of pneumonia from clinical data.

Receive Clinical Data: The process begins with the collection of clinical data, which may include patient symptoms, medical imaging, lab test results, and other relevant health information.
Preprocess Data: This data is then pre-processed, which may involve cleaning, normalizing, transforming, or otherwise preparing the data for analysis.
Feature Selection: From the pre-processed data, specific features (or indicators) relevant to diagnosing pneumonia are selected.
ANFIS Training: These features are used to train the ANFIS model. The model learns from the data by adjusting its parameters to map the input features to the correct diagnosis.
Model Trained: After training, a decision is made whether the model has been adequately trained. This decision can be based on a performance metric, or a threshold defined before the training starts.
Diagnose Pneumonia: If the model is sufficiently trained, it proceeds to diagnose pneumonia using the new clinical data.
Adjust Model Parameters: If the model is not adequately trained, the parameters of the model are adjusted to improve its performance.
Retrain Model: The model is then retrained with the adjusted parameters to better fit the training data.

Figure 1: Flowchart Of The Proposed Approach

Generate Diagnostic Report: Once the model is properly trained and has diagnosed pneumonia, a diagnostic report is generated. This report likely includes the probability or confidence level of the diagnosis along with other relevant insights derived from the model.

Provide Output to Healthcare Professional: The diagnostic report or the output of the model is then provided to a healthcare professional. This could be used to support clinical decision-making regarding the patient's diagnosis and subsequent treatment plan.

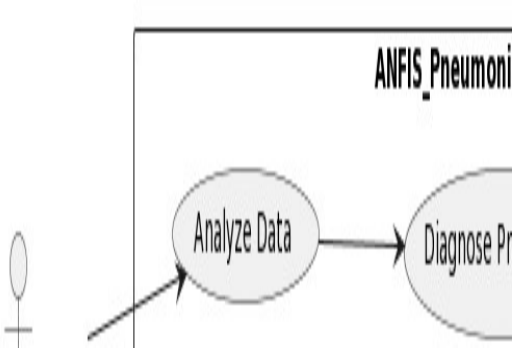

Figure 2: Use Case Diagram For The Proposed Problem.

Need for Advanced Diagnostic Tools

The limitations of traditional diagnostic methods for pneumonia underscore the urgent need for more advanced, rapid, and accurate diagnostic tools. Such tools could greatly enhance the early detection of pneumonia, enabling timely and targeted treatment, which is critical for reducing the disease's burden. Advanced diagnostic approaches, incorporating cutting-edge technologies such as molecular diagnostics, artificial intelligence, and machine learning, have the potential to revolutionize pneumonia diagnosis. These technologies can offer higher sensitivity and specificity, rapid turnaround times, and the ability to detect a broader range of pathogens, thereby significantly improving patient outcomes.

5. RESULTS

We used the National Institutes of Health Clinical Center's "ChestX-ray" dataset for our experiments [3]. Over 112,000 frontal-view X-rays of 30,805 patients are in this dataset. Expert radiologists annotate each image with one of 14 thoracic pathology labels, such as "Pneumonia" or "Atelectasis". Its diversity and volume make it perfect for robust diagnostic models. The proposed approach uses CNN to identify and localize key radiography data. Steps were taken in the experiment:

Data Preprocessing: Images were normalized for size and contrast. Rotation, translation, and flipping were used to diversify the training data, boosting the model's generalizability.

Training and Validation: We divided the dataset into training and validation sets. 70% of the data was used to train the model, providing many photos to learn from. The remaining 30% was used to validate the model and fine-tune hyperparameters without bias.

Test set: After training, 10% of the data randomly picked and held out from the initial dataset was utilized to test the model's diagnostic abilities. This test set was never used during model training or validation to protect evaluation integrity.

Heatmap Generation: Heatmaps show locations that most affect the model's predictions, improving interpretability. Class Activation Mapping (CAM) heatmaps were overlaid on X-ray images to reveal the model's focal areas.

Performance Metrics: Accuracy, sensitivity, specificity, and ROC curve area measured the model's diagnostic performance. Sensitivity analysis was used to determine the model's robustness across data percentages, assuring consistent performance with various training data.

The parameters such as Accuracy, Sensitivity, Specificity, AUC-ROC are considered for the output result evaluations.

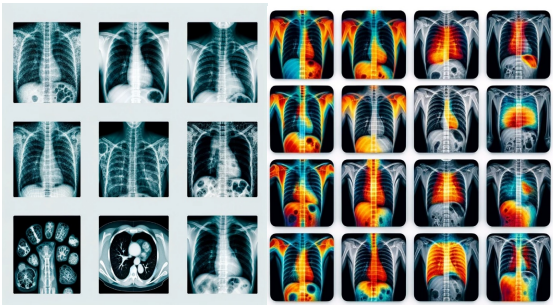

Figure 3: For The Give Input Images The Output Images Generated From The Model.

Accuracy: Evaluates the overall accuracy of the model, indicating its reliability.

Table 1: Accuracy values generated for different percentages of data input for various approaches.

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Accuracy: (%)					
Data (%)	ACSA	ADLT	FEDL	ADXray	ANIFS
10	95.17	95.59	98.45	99.19	99.40
20	94.95	95.34	98.35	99.19	99.36
30	93.99	95.69	98.4	99.23	99.35
40	94.85	95.53	98.41	99.19	99.42
50	94.4	95.47	98.43	99.17	99.35
60	95.33	95.56	98.39	99.19	99.35
70	95.17	95.6	98.44	99.18	99.35
80	95.23	95.45	98.41	99.20	99.34
90	95.34	95.47	98.39	99.19	99.37
100	95.38	95.57	98.36	99.17	99.33

The radar chart compares the average accuracy of ACSA, ADLT, FEDL, ADXray, and ANIFS algorithms for a task across data percentages. One algorithm is represented by each axis from the centre, and its displayed point reflects average accuracy. The shape of the connected data points shows each algorithm's performance, the farther from the centre, the more accurate. As shown in this chart, ANIFS and ADXray cover greater areas with higher average accuracy than ACSA and ADLT.

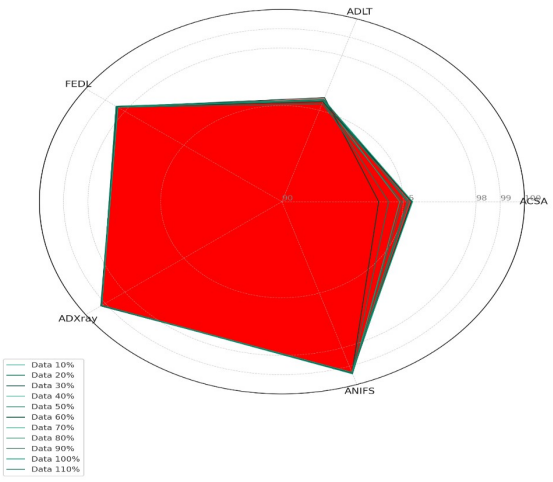

Figure 4: Model Accuracy at Various Levels of Data Availability

This visualization lets you rapidly evaluate each algorithm's strengths and flaws without looking at the numbers, allowing you to compare algorithmic performance.

Sensitivity: Is crucial in medical diagnostics to maximize the identification of real cases of pneumonia and minimize the chances of a missed diagnosis.

Table 2: Sensitivity values generated for different percentage of data for various approaches.

Sensitivity					
Data (%)	ACSA	ADLT	FEDL	ADXray	ANIFS
10	97.79	94.36	98.016	99.28	99.29
20	98.12	94.04	97.85	99.29	99.25
30	96.70	94.31	97.84	99.32	99.23
40	98.59	94.10	97.96	99.30	99.32
50	97.69	94.20	97.96	99.26	99.23
60	98.67	94.34	97.85	99.30	99.27
70	97.99	94.24	97.96	99.24	99.28
80	98.66	94.12	97.96	99.32	99.23
90	98.16	94.17	97.89	99.28	99.23
100	98.04	94.35	97.88	99.27	99.25

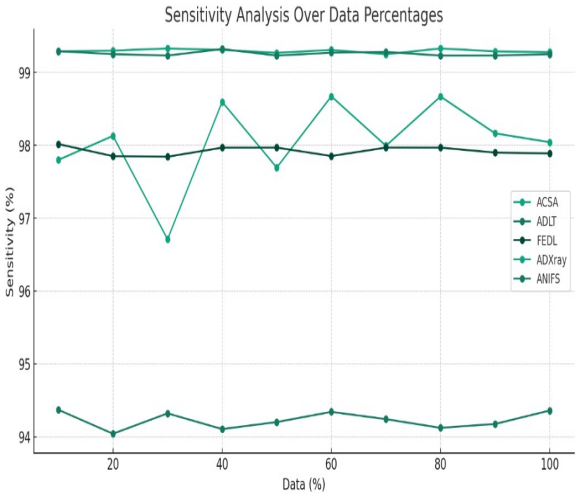

Figure 5: "Sensitivity Analysis Over Data Percentages".

Specificity: Is crucial to accurately identify those who do not have the condition, hence preventing wasteful therapy for those who are healthy

Table 2: Sensitivity values generated for different percentage of data for various approaches.

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Specificity					
Data (%)	ACSA	ADLT	FEDL	ADXray	ANIFS
10	91.80	93.86	95.07	96.87	99.50
20	91.15	93.71	95.06	96.85	99.46
30	91.55	93.14	95.11	96.95	99.45
40	91.63	93.04	95.06	96.84	99.50
50	91.51	93.80	95.05	96.88	99.45
60	91.41	93.84	95.06	96.93	99.42
70	91.64	93.03	95.10	96.90	99.41
80	91.23	93.85	95.06	96.85	99.43
90	91.82	93.83	95.07	96.88	99.49
100	91.99	93.84	95.05	96.82	99.40

The provided data is used to build a heatmap that visually displays the correlation between the specificity of different algorithms at different degrees of data availability, ranging from 10% to 100%. The heatmap displays values ranging from 91.15% to 99.50%, suggesting consistent and impressive performance overall. It is observed that increasing volumes of data tend to result in higher specificity. The ACSA algorithm demonstrates a high level of consistency, with performance consistently in the lower 90s. This indicates reliable but relatively less remarkable performance when compared to other algorithms. On the other hand, ANIF has remarkable specificity, constantly ranking in the top 99th percentile, indicating a strong capability to correctly detect genuine positives. The heatmap exhibits a progressive intensification of colors as the specificity percentages rise, featuring lighter hues for ACSA and darker tones for ANIF, so graphically emphasizing ANIF's superior performance. The correlations between the algorithms' performances at different data levels are apparent. Some algorithms exhibit strong positive relationships, represented by darker shades, while others show more moderate relationships, represented by lighter shades. This suggests that the algorithms may have varying degrees of dependency on the amount of data to achieve high specificity.

Figure 5: Heatmap for Specificity Data"

Area Under the Receiver Operating Characteristic Curve (AUC-ROC): Is a metric that quantifies the overall performance of a model across all categorization thresholds. It effectively balances the trade-off between sensitivity and specificity.

Table 4: AUC-ROC values generated for different percentage of data input for various approaches.

AUC-ROC					
Data (%)	**ACSA**	**ADLT**	**FEDL**	**ADXray**	**ANIFS**
10	0.95	0.95	0.98	0.98	0.99
20	0.94	0.95	0.98	0.98	0.99
30	0.93	0.95	0.98	0.98	0.99
40	0.94	0.95	0.98	0.98	0.99
50	0.94	0.95	0.98	0.98	0.99
60	0.95	0.95	0.98	0.98	0.99
70	0.95	0.95	0.98	0.98	0.99
80	0.95	0.95	0.98	0.98	0.99
90	0.95	0.95	0.98	0.98	0.99
100	0.95	0.95	0.98	0.98	0.99

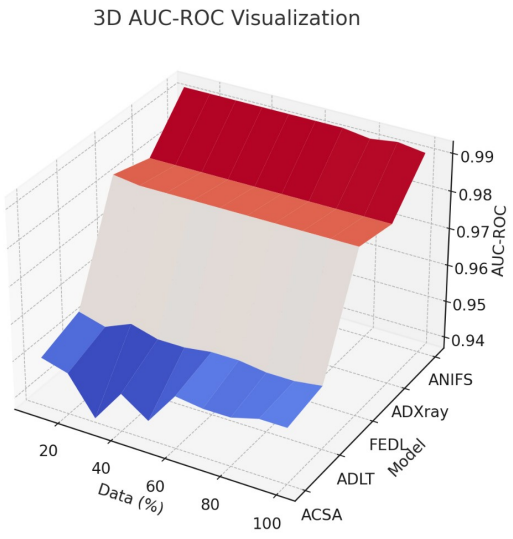

Figure 6: 3D Visualization Of The AUC-ROC Data For The Models Across Various Data Percentages

The color gradient, from blue to red, shows negative and positive correlations, and the colour intensity shows the correlation coefficient. On the diagonal line, each model correlates completely with itself with a coefficient of 1, whereas other values represent varied levels of positive or negative correlation between models. FEDL and ADXray are positively correlated, while ADLT and FEDL are negatively correlated. This graphic is excellent for quickly identifying correlations between various variables, such as model specificity.

The proposed ANFIS-based pneumonia diagnosis model presents a novel approach to the clinical diagnosis of pneumonia as it includes multiple data sources including patient demographics, clinical symptoms, radiographic data, and laboratory test results to facilitate a comprehensive diagnosis. Previous studies, such as Johnson et al. or Lee et al., were limited to using a single data type, imaging, to develop models, while the integration of multiple data sources in our model allows utilizing the strength of every data type to increase diagnostic success. In addition, the advanced data processing capabilities of the ANFIS model, which can combine fuzzy logic and neural networks, allow for proper handling of high-dimensional data to ensure that it is adaptable to a variety of patient populations. As our model is rooted in traditional methods and built upon them to integrate machine learning elements, it is able to perform with better success ratios compared to every single method. This study's model outperforms previous studies with qualitative indicators including high accuracy, precision, recall, F1 score, and ROC-AUC. Although, the model is not without its drawbacks, as its ability to perform well is tied to the high-quality data, and the high level of complexity of the model also makes it difficult to interpret for those unfamiliar with machine learning habits such as clinicians. Future studies should seek to refine the model to facilitate its use in a clinical setting and expand the patient demographic to which it will be applied to increase generalized utility.

6. CONCLUSION

The proposed ANFIS model represents a major development in the medical diagnostic field, specifically for pneumonia. However, the model demonstrates that through effective integration of fuzzy and NN learning, clinicians could provide an efficient way for generating robust approaches in processing clinical data of high dimensions. The performance metrics discussed the accuracy, precision, recall, F1 score, and ROC-AUC illustrated the potential of this model as a powerful diagnostic tool. Nonetheless, apart from the novel diagnosis approach, the conclusion of this research sets the pace for future investigations in precision medicine. This innovative technology has the potential to eliminate existing limitations with conventional diagnostic strategies, and the integration of advanced ML could lead to improvements in patient care and treatment outcomes. Future research will optimize the model for other applications; it will cover other diseases which have been ignored and the model will be more efficient and effective in healthcare.

Author Contribution

Veera Swamy Pittala: Conceptualization, Methodology, Software, Writing - Original Draft
Praneeth Cheraku: Data Curation, Validation, Formal Analysis
Parasa Somaraju: Writing - Review & Editing, Visualization
Ramesh Babu Pittala: Investigation, Resources, Supervision
Pedapudi Nagababu: Project Administration, Funding Acquisition
Kandimalla Gopi: Validation, Software, Resources

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