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DEEP LEARNING-BASED ENSEMBLE APPROACH FOR LUNG DISEASE CLASSIFICATION USING CHEST X-RAY IMAGES

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Abstract
Recent technologies development makes it possible to apply artificial intelligence-based techniques in nearly all areas of life. The exactness of deep learning models enables the medical industry to identify and classify a wide a broad range of illnesses. Chest X-rays are prescribed to be safe for diagnosis in a number of circumstances because to the high contagiousness of COVID-19. Among the leading causes of disease and morality worldwide is lung disease, which includes a respiratory infection, TB, and Chronic Obstructive Pulmonary Disease (COPD). For better patient outcomes and efficient treatment, an early and precise diagnosis is essential. However, radiologists and physicians frequently use manual interpretation for classic diagnostic techniques like X-rays, CT scans, and laboratory testing, which can be laborious and prone to human mistake. Deep learning techniques have proven more and more successful in automating and enhancing the reliability of medical diagnostics. This research proposed an ensemble model by incorporating the capabilities of convolutional neural networks and gated recurrent unit to enhance performance for lung disease classification using chest X-rays images. The performance of proposed model is assess by employing the lung disease dataset and compared with other deep learning models such as, Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN). By using the CNN features extraction capabilities and Gated Recurrent Unit (GRU) sequential learning efficiency, the ensemble model outperformed in term of accuracy (0.9721), precision (0.9731), recall (0.9721) and F1score (0.9719). These findings shows the effectiveness of proposed model to improving the accuracy of lung diseases identification.

INTRODUCTION

In medical images, a computer vision grabs much attention particularly in the interpretation of X-ray images and the identification and categorization of lung abnormalities. This method helps identify lung infections including pneumonia and tuberculosis by identifying several visual criteria like texture, shape, and intensity [1]. By improving the regions of interest on X-rays, CV methods including feature extraction, segmentation, and edge identification offer important insights into lung architecture and potential disease markers. These methods would maximize the detection of extremely minute variations in medical pictures that could be hard to notice and would need complex calculations for proper interpretation. Through the use of Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) and other deep learning algorithms, computer vision diagnostic tools have advanced in ensemble learning [2].

By utilizing multiple paradigms instead of relying solely on one, the techniques utilized improve predictive power and provide improved accuracy and dependability of the diagnostic results, even in cases where the patient's anatomy or the quality of the images acquired varies [3]. The most useful characteristics about the data are captured by many modeling techniques, which may contain subtle patterns and correlations that are easily overlooked by a single program [4].

By recognizing the symptoms of lung disorders from chest X-ray pictures, deep learning models are crucial in helping medical personnel discover these conditions [5]. When trying to identify lung disorders in their early stages, non-linear models are unable to assess a large number of potentially complicated non-linear patterns in the X-ray data. Genetic algorithms (GAs) are optimization technique that utilize to evaluate with huge evidence spaces [6]. However, they encounter difficulties in preserving efficiency and stability when exploring vast solution spaces, particularly when the datasets are dynamic and complicated in terms of imaging. This issue typically arises with simulated annealing as well [7]. Another optimization technique such as Coati optimization, were tested to adjust ensemble learning parameters for the identification of lung diseases. By making the optimization dynamic, this approach enables the optimization of extremely complicated medical imaging data to improve the accuracy of the created models in identifying minute illness signs in chest X-rays[8]. This phase increases the diagnosis's accuracy capabilities, which in turn makes it a far better, more reliable, and quicker tool for health professionals to use while making clinical decisions in real time [9].

This research is to provide scalable and real-time diagnostics by using ensemble learning approaches to increase the accuracy and reliability of lung disease detection across chest X-ray images [10]. The contribution of this research are as follows:

- This research proposed an ensemble model based on the Convolutional Neural Networks (CNN) and Gated Recurrent Unit (GRU) for accurately predict the lung disease classification using chest X-rays images.
- To ensure model stability and enhance data quality, preprocessing method such image normalization, scaling, and augmentation were applied.
- The proposed ensemble model is evaluated using the evaluation parameter such as accuracy, precision, recall and F1 score.
- Comparison is performed based on different deep learning models such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), and Convolutional Neural Networks (CNN) to evaluate and diagnosis diseases.

The rest of the paper is organize as follows: Section 2 explains the related work that are relevant to the proposed methodology. Section 3 presented the research methodology in which the ensemble deep learning model is proposed. Section 4 discusses the results and discussion. Section 5 represent the conclusion and future work of this research.

2. Related Work

Technological advancements have made medical imaging data much more accessible, which has substantially aided in the detection of some lung disorders [11]. Chest X-rays are very helpful in showing the phases of lung disorders and supporting the first lung evaluation, which significantly influences the treatment's result [12]. However, the challenges posed by variations in picture quality, subtle aberrant findings, and the degree of competence required make it difficult to use chest X-ray films for the diagnosis of lung illnesses [13]. Strong evidentiary techniques for evaluating and categorizing lung disorders from X-ray pictures are desperately needed by many medical practitioners, since many patients today suffer from the detrimental consequences of delayed, accurate diagnosis [14]. Combining various source data with ensemble learning models will likely resolve most of the issues in a sophisticated imaging environment, allowing medical practitioners to assess imaging data more effectively and make better diagnoses [15].

Deep learning resulted in a revolution in the processing of chest x-rays, which has been used to provide automated and precise diagnosis for a variety of illnesses, including pneumonia, COVID-19, and other lung ailments [16]. Additionally, deep learning can accurately segment and classify abnormalities by extracting complicated information from X-ray pictures. Voice hybrid models with a transformer and attention com-ponent have significantly improved in accuracy and interpretability [17]. In terms of reducing diagnostic errors and accelerating the radiological workflow, deep learning has made significant contributions to the field of medical imaging [18].

Convolutional neural networks offer extremely accurate diagnosis and categorization of a variety of ailments, they are typically used for viewing and interpreting chest X-ray pictures [19]. CNNs are ideal for medical imaging applications because they provide an automatic learning hierarchy of the feature spaces, including the detection of edges, textures, and more complex structures in pictures. In general, a number of CNN architectures are employed for the categorization of chest X-rays in order to identify certain disorders, such as viral pneumonia, lung opacity, and normal pneumonia [20]. But in rare cases, CNNs will be able to correctly diagnose irregularity utilizing a sizable annotated dataset, transfer learning, and data augmentation approaches. Grad-CAM-style methods for locating regions pertinent to X-ray analysis are also included in this category [21].

Artificial neural network model can correctly identify a variety of lung conditions, including viral pneumonia, common pneumonia, and lung opacity [22]. Convolutional neural networks have the potential to replace human features engineering since they can automatically extract the most significant features from X-ray pictures. An ANN can accurately differentiate between healthy and sick chest X-ray pictures when a sizable dataset is properly trained [23]. In order to work with radiologists to diagnose patients more quickly and accurately, it is likely that the differentiating performance of ANN models will be improved in conjunction with the assistance of certain contemporary approach-es like transfer learning and data augmentations whenever are used in classification process [24].

The use of long short-term memory models for chest X-ray analysis has undoubtedly increased, particularly in automated illness detection and diagnostic applications that distinguish between viral pneumonia, lung opacity, and normal pneumonia [25]. CNN is often and successfully used for feature extraction, but it can also be used with picture data to find spatial correlations and sequential patterns. Therefore, an LSTM layer is typically employed to assess spatial correlations in many picture areas, whereas a CNN is typically utilized for feature extraction [26]. By utilizing the LSTM's capacity to preserve long-range dependencies, this method improves classification accuracy and model performance. When it comes to identifying anomalies from chest X-rays to aid in early diagnosis and treatment choices, these models appear promising [27].

While CNN's superiority usually applies to image-based applications, RNNs in conjunction with constructions like LSTMs or GRUs can help ongoing research into defining temporal correlations in medical scan sequences [28]. The diagnosis of spatial-temporal correlations between X-ray image characteristics aided by a hybrid model that combines CNN and RNN. The technique worked well for applications that allowed the investigation of changes in lung conditions in multiple imaging frames, such automated lung opacity and the distinction between normal and viral pneumonia [29]. It serves as a database of equations for the typical production process.

A deep neural network CNN model that uses both local and global features to segment pixels. By implementing significant changes to the training procedure and a new post-processing step that combines bounding boxes from several models, this model achieves robustness accuracy was 89.60% [30]. A capsule network-based model with a 93.20% accuracy rate for classifying lung cancer from medical imaging data. In contrast to conventional CNNs, their method used capsule networks to better capture spatial hierarchy in tumor characteristics [31]. The scientists pointed out that although the model performed well in identifying cancerous lesions, capsule networks are still computationally intensive, which may restrict their use in real-time clinical settings. Although more optimization is required to increase efficiency for widespread diagnostic

application, this research advances deep learning techniques for early lung cancer diagnosis [32].
A deep learning method with 90.40% accuracy for classifying lung cancer using InceptionV3 with feature extraction [33]. Their approach improved diagnostic performance on medical imaging data by efficiently leveraging the multi-scale feature learning capacity of the InceptionV3 architecture [34]. The low interpretability of the Inception modules, which lowers clinical transparency in decision-making, was noted as a major weakness [35]. While highlighting the urgent need for more explainable AI systems in medical image analysis to promote physician trust and adoption. This study is consistent with continuing efforts to employ sophisticated deep learning models in tumor diagnoses [36]. Some Other research with limitation and research Gap is shown in Table 1.

Table 1: Related Work

Authors	Approach	Limitation/GAP	Accuracy
[37]	CoroNet CNN model for COVID-19 detection	Limited generalizability; trained on small dataset	89.60%
[38]	Capsule Network for tuberculosis detection	Capsule networks are computationally demanding	93.20%
[39]	InceptionV3 with feature extraction for lung disease	Limited interpretability of Inception modules	90.40%
[40]	Bi-LSTM with feature extraction for lung diseases	Complexity in training due to LSTM layers	89.50%
[40]	Deep CNN with data augmentation for lung cancer	Limited diversity in training dataset	91.30%

3. Research Methodology

Lung cancer is typically performed with the aim of diagnosing lung conditions such as COVID-19, pneumonia, and others. These films could show abnormal outline from fluid accumulation, tumors, or lung infections. Among other advanced image processing technologies, edge detection and segmentation techniques are employed to indicate the presence of disease indicators. In this research, the model is trained and evaluated using a dataset of classified chest X-ray imagery that additionally included images of lung illnesses. Image normalization, scaling, and augmentation are examples of procedures that improve data quality and fortify the model. The X-ray pictures were characterized using edge detection and segmentation algorithms in order to effectively detect illness signs. The deep learning models have been employed, such as convolutional neural networks, recurrent neural networks, long short-term memory and artificial neural networks. The evaluation metrics is used such as accuracy, precision, recall, and f1 score utilization have been used to assess the model's performance. A confusion matrix has been created, and the model's diagnostic capabilities were measured through training and loss plotting. A hybrid model based on CNN and GRU is proposed to enhance the diagnostic outcome. Figure 1 shows the research methodology.

3.1 Dataset

Lung disorders are caused by a number of causes, including lifestyle choices, genetic predispositions, environmental variables, and different types of infections. An essential collection of X-ray pictures for the diagnosis and identification of all lung conditions is the lung x-ray image dataset. The lung x-ray image dataset includes high-quality x-ray pictures that were meticulously gathered from many sources, including clinics, hospitals, and other healthcare facilities. There are 3,475 x-ray pictures in the entire collection in which 1250 images demonstrate lung health and act as a standard by which to compare diagnosis processes. Furthermore, 1125 images lung opacity shows the X-ray images with different degrees of lung problems, offering a range of study scenarios.

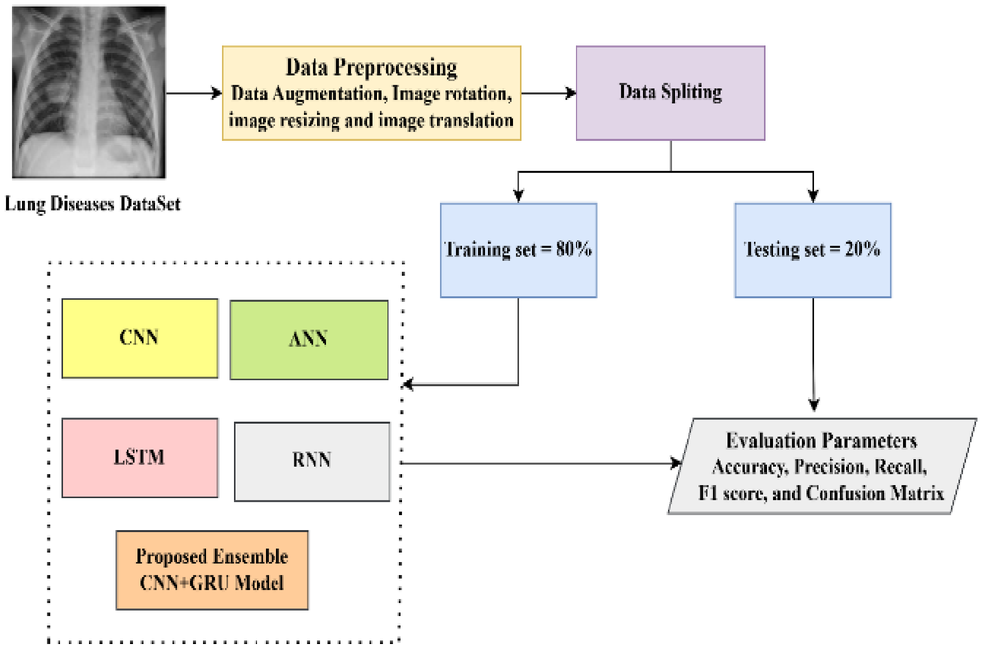

Figure 1. Proposed Methodology

Another, 1100 images associated with cases of viral pneumonia helps to identify and understand this particular lung ailment. This dataset features a larger collection on a range of x-ray images to help the medical professionals detect, categorize, and diagnose different lung issues. The dataset is useful for enhancing respiratory medicine re-search and therapeutic outcomes.

3.2 Deep Learning Models

The development of deep learning has transformed the study of chest X-rays, making it possible to automatically and accurately diagnose a number of pulmonary diseases, such as COVID-19, pneumonia, and lung cancer. These sophisticated methods greatly enhance abnormality segmentation and classification performance by successfully identifying complex patterns in radiography pictures. A variety of architectures, including CNN, ANN, LSTM, and RNN, are implemented and evaluated in this study due to the proven efficacy of deep learning in medical image analysis. Our suggested hybrid CNN+GRU model is intended to improve feature extraction and sequential pattern recognition in chest X-ray interpretation. A strong method for detecting pulmonary diseases from medical imaging data is provided by combining GRU's temporal processing skills with CNN's spatial feature learning.

3.3.1 Convolutional Neural Networks

The majority of the time, chest X-ray images are observed and analyzed using deep learning models, such as Convolutional Neural Networks (CNNs), which are very accurate in diagnosing and classifying various ailments. CNNs can learn hierarchical features, such as the recognition of edges, textures, and complex structures in the images, automatically from the images, making them very useful for medical image analysis. Generally, different CNN architectures are used for chest X-ray classification to define some conditions, such as viral pneumonia or the detection of lung opacity and normal pneumonia. CNN may identify abnormalities with high accuracy by using large annotated datasets, transfer learning techniques, and data augmentation. Additionally, Grad-CAM-type techniques help identify important regions for X-ray analysis by medical professionals. This explains a basic CNN architecture that is used to categorize chest X-ray images. The Confusion matrix shown in Figure 2 and mathematical formulation shows in Equation 1.

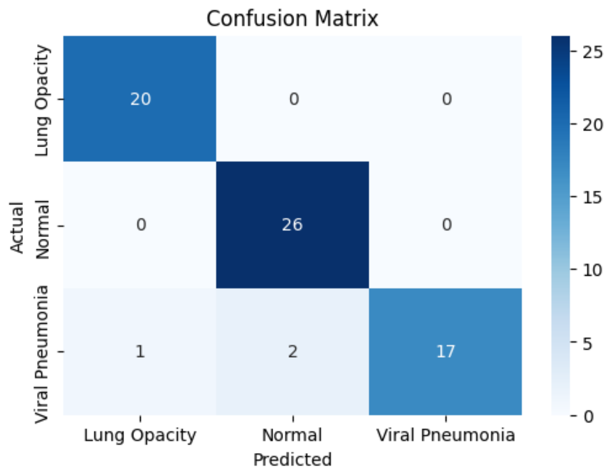

Figure 2: Confusion Matrix of CNN Model.

$$Y = f(W * X + b) \quad 1$$

The matrix of pixel values called *X* represents the input chest X-ray pictures. *W* stands for the learnt filters, or kernels. The bias term is *B*. An activation function is *f*.

3.3.2 Artificial Neural Network

Artificial Neural Network (ANN) model can correctly identify many lung diseases, including viral pneumonia, normal pneumonia, and lung opacity, while analyzing chest X-ray images. Convolutional Neural Networks (CNNs), one type of deep learning architecture, have the ability to replace human features engineering as they are able to automatically extract important features from X-ray images. ANN may be able to accurately distinguish between normal and diseased chest X-ray with the usage of large dataset training. ANN models can further improve the classification performance and assist radiologists in making faster and more accurate patient diagnoses when combined with state-of-the-art techniques like data augmentation and transfer learning. The confusion matrix shows in Figure 3 and mathematical formulation shows in Equation 2.

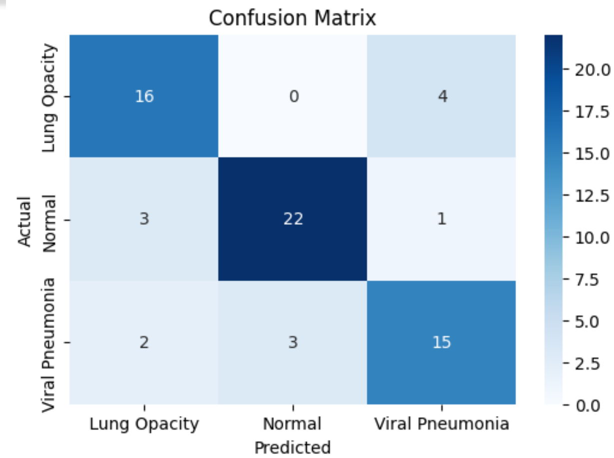

Figure 3: Confusion Matrix of ANN Model.

$$y = f(\sum_{i=1}^{n} wixi + b) \quad 2$$

Where *xi* represent the input features, *wi* represent the appropriate the weights, *b* represents the bias term, *f* represent the activation function.

3.3.3 Long Short-Term Memory

Long Short-Term Memory (LSTM) models have become more popular for the analysis of chest X-ray images, particularly for automated disease detection applications such as the categorization of viral pneumonia, lung opacity, and normal pneumonia. CNN commonly used for feature extraction in image data, LSTM also be utilized to identify sequential patterns and spatial correlations. Typically, a CNN for feature extraction and an LSTM layer to analyze spatial correlations across many image regions. This approach increases classification accuracy and model performance by taking use of the LSTM ability to maintain long-range dependencies. These models have shown promising results in detecting abnormalities in chest X-rays, assisting in early diagnosis and clinical decision making. The confusion matrix shows in Figure 4 and the mathematical formulation shown in Equation 3.

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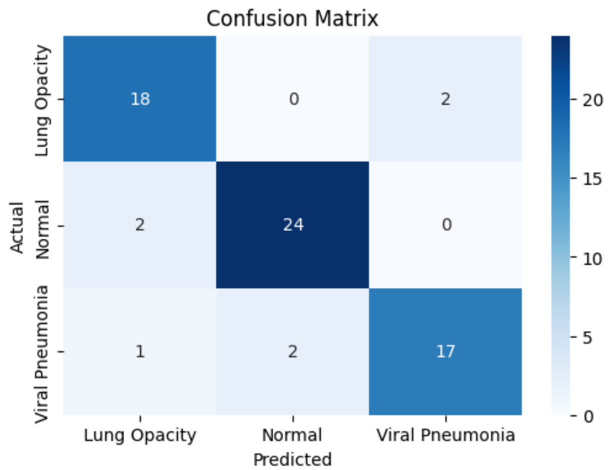

Figure 4: Confusion Matrix of LSTM Model.

$$h_t = O_t \odot tanh(c_t) \quad 3$$

The equation ht=ot represent the LSTM hidden state update, ot represent the control of state, moved to the following phase application of tanh activation.

3.3.4 Recurrent Neural Network

To obtaining sequential and temporal characteristics from X-ray of the chest. RNNs, particularly when combined with architectures like LSTMs or GRUs can assist in assessing temporal correlations in medical scan sequence, such as tracking the progression of an illness over time, even though CNN are often better suited for images-based applications. RNNs and CNNs can be used in hybrid model to improve diagnosis by finding spatial-temporal correlations in X-ray image characteristics. This method works very well for applications that enable the study to changes in in lung conditions across several imaging frames, such as automated lung opacity and the differentiations between viral and normal pneumonia. The standard pro-duction process involves a collection of equations. The Confusion Matrix shows in Figure 5 and the RNN formula shows in Equation 4.

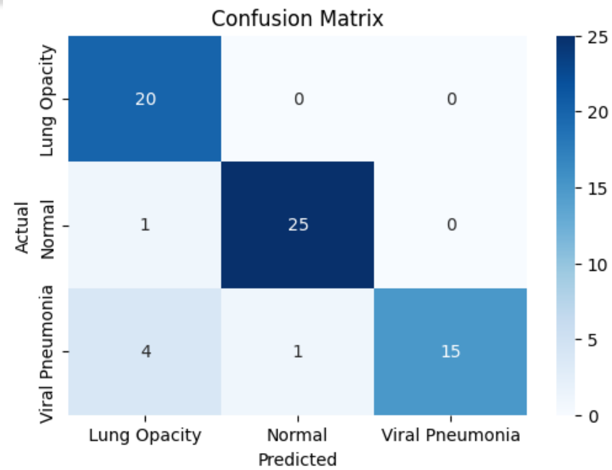

Figure 5: Confusion Matrix of RNN Model.

$$yt = g(W_y h_t + b_y) \quad 4$$

The output at time step *t* is denoted by *yt*. By is the bias; *g* is the activation function, such as sigmoid in a binary classification issue or SoftMax in a multi-class classification problem; and *Wy* is the output weight matrix.

3.3.5 Proposed Ensemble Model

The proposed ensemble CNN+GRU model for chest X-ray assessment combines the strengths of both architectures to optimize sequential pattern recognition and attribute extraction. The GRU layer iteratively reviews all these feature maps for temporal correlations, improving classification accuracy, while the CNN portion efficiently gathers spatial information from X-ray images, revealing significant patterns like lung abnormalities. By combining various CNN+GRU models, the technique reduces overfitting, improves di-agnostics, and increases generalization and robustness. By learning complex representations from the chest X-ray dataset, the hybrid model aims for enhanced growth oriented toward a reliable and accurate automatic identification of pulmonary diseases like viral pneumonia, pneumonia, and typical pneumonia. The proposed model confusion matrix shows in Figure 6 and mathematical formulation shown in Equation 5.

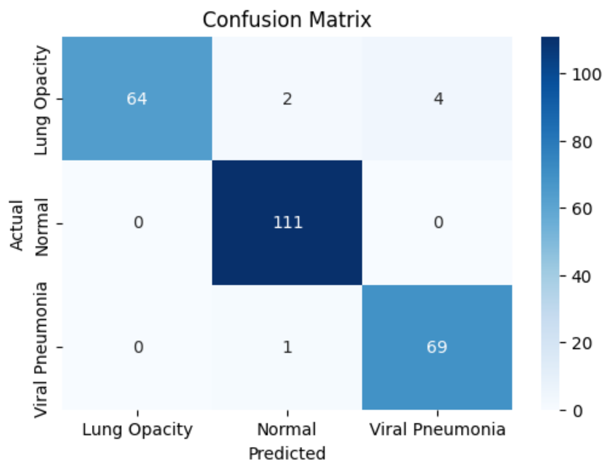

Figure 6: Confusion Matrix of Ensemble Model.

$$h_t = (1 - Z_t) \odot h_{t-1} + Z_t \odot \widetilde{ht} \quad 5$$

The gated recurrent unit in the proposed ensemble by incorporating CNN and GRU model capabilities for interpretation of chest X-rays ensures that the convolutional neural network retrieves the spatial information by learning sequential correlations. *ZT* determine how much historical data should be retain, *rt* controls the influence of previously hidden state. *Ht* represent the combined with the previously concealed state (*ht-1*) to construct the current hidden state (*ht*).

4. Results and Discussion

The results and discussion section provides a comprehensive analysis of the findings, evaluating the effectiveness of the proposed approach using key performance metrics, including accuracy, precision, recall, and F1-score. While precision evaluates the model's capacity to reduce false positives by computing the ratio of genuine positives to all predicted positives, accuracy quantifies the percentage of correctly classified occurrences across all forecasts. Conversely, recall is the ratio of true positives to actual positives that indicates the model's capacity to find all pertinent instances. Convolutional neural network, artificial neural network, long short-term memory, and recurrent neural network are the deep learning architectures that we implement and compare in this study. Our suggested ensemble model based on CNN and GRU models performs better than the others.

4.1 Performance of CNN Model

The CNN model outer performed the others in the classification contest, achieving better result. The accuracy (0.9545) after with 25 epoch showed the model exceptional capacity for generalizations. The model's precision of (0.9574) indicates that the can reliability recognizes positive occurrence, and its recall (0.9545) indicates that it can identify relevant patterns without generating a large number of false negatives. Figure 7 display the performance of CNN model.

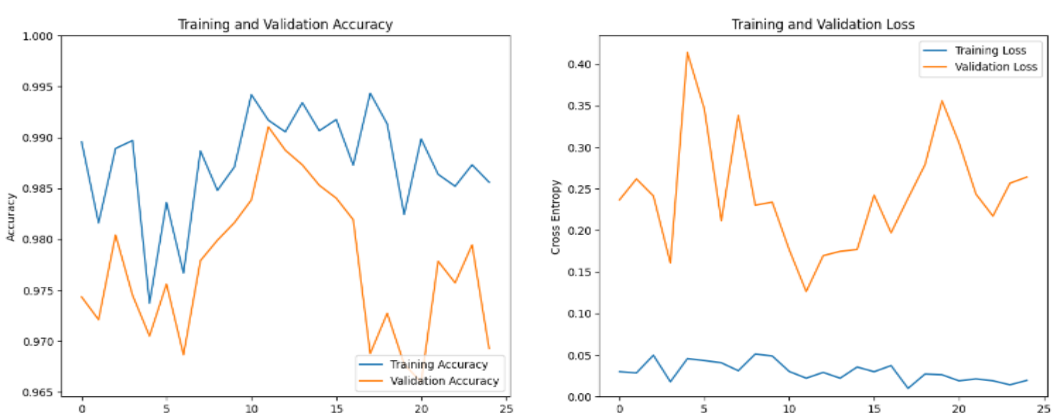

Figure 7: Accuracy and Loss of CNN Model.

4.2 Performance of ANN Model

The Artificial Neural Networks (ANN) demonstrated remarkable performance with accuracy (0.8031) through 25 Epoch in the classification tasks. With precision (0.8048), recall (0.8032), f1 score (0.8036) respectively, the model was demonstrated to be well balanced. Additionally, its predictive power all metrics. This result showed the ANN may improve generalization and highlight important data trends. Figure 8 shows the accuracy and loss plot.

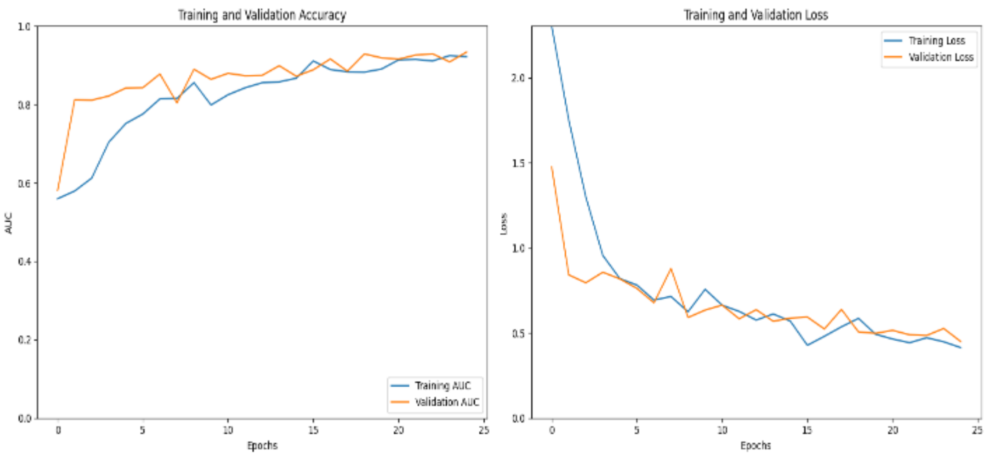

Figure 8: Accuracy and Loss of ANN Model.

4.3 Performance of LSTM Model

The long short-term memory model performed exceptionally well in the classification tasks, with an accuracy of (0.8939). The effectiveness of model is further demonstrated by their well-balanced classification abilities, which are demonstrated by their precision (0.8994), recall (0.8939), f1 score (0.8938). The obtain results of LSTM are displayed Figure 9.

Figure 9: Accuracy and Loss of LSTM Model.

4.4 Performance of RNN model

The RNN model perform well in the classification with an accuracy of (0.9091) in 30 epoch. The model demonstrates a high percentage of correctly predicted positives events among all anticipated positives, with a precision of (0.9242), recall (0.9091), and f1 score (0.9079). The performance of RNN model is displayed Figure 10.

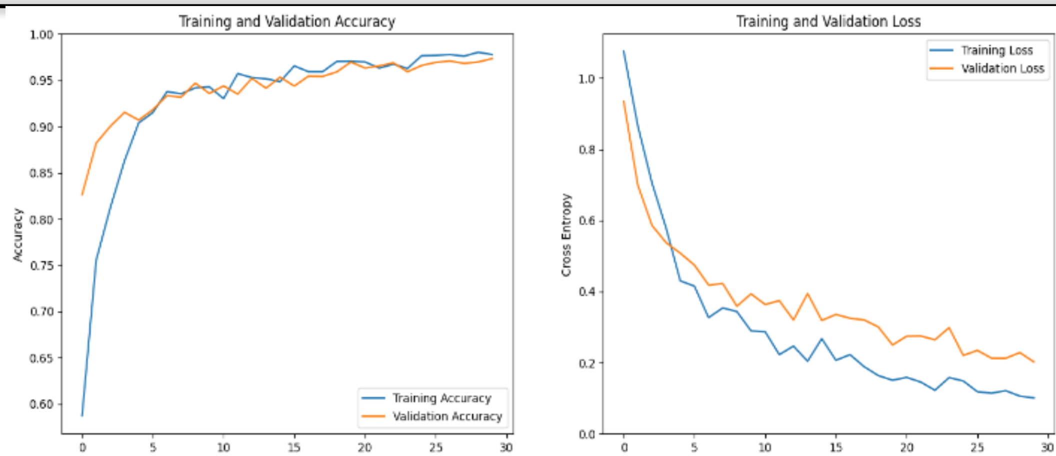

Figure 10: Accuracy and Loss of RNN Model.

4.5 Performance of Proposed Ensemble Model

The proposed ensemble convolutional neural network + gated recurrent unit model outer performs the others on classification task according to evaluation criteria. The model impressive accuracy (0.9721), precision (0.9731), recall (0.9721), and f1score (0.9719) with 30 epoch. The performance of the proposed models shows the accuracy and loss plot of proposed models is displayed Figure 11. These result shows how effectively GRU sequential learning capabilities and CNN features extraction abilities combine to create the ideal model.

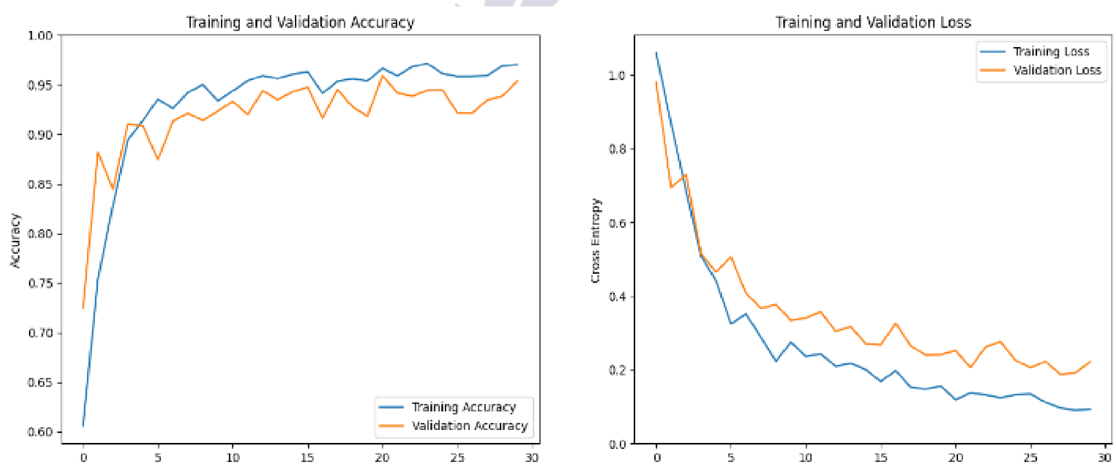

Figure 11: Accuracy and Loss of CNN+GRU Models.

4.6 Performance Analysis of All Models

The research demonstrates the performance of each model, including CNN, ANN, RNN, and LSTM over variety of dataset and topologies. Although each model has unique advantages, each of them performance better than the other in every situation: simple classification tasks are handled by ANN, spatial information is effectively extracted by CNN, vanishing gradient issue are handled by LSTM, and sequential relationships are found by RNN. The proposed CNN+GRU ensemble model improves accuracy and generalization by utilizing both CNN's feature extraction talents and GRU's capacity to sustain long-term relationships. Through enhanced feature representation and sequential pattern learning, ensemble model outperformed as compare to individuals' models in classification. Table 4.1 presents the findings from the analysis of all models.

Table 4.1: Analysis of All Employed Models

Models	Accuracy	Precision	Recall	F1 score
CNN	0.9545	0.9574	0.9545	0.9534
ANN	0.8031	0.8048	0.8032	0.8036
LSTM	0.8939	0.8994	0.8939	0.8938
RNN	0.9091	0.9242	0.9091	0.9079
Proposed Ensemble Model	0.9721	0.9731	0.9721	0.9719

5. Conclusion and Future Work

Diagnosis of pulmonary and cardiothoracic illness depends on the interpretation of the chest x-rays. The research proposed a deep learning-based ensemble approach using CNN and GRU for lung disease classification using chest x-ray images. The proposed model compare with the variety of deep learning models such as artificial neural networks, long short-term memory, convolutional neural networks and recurrent neural networks were used to evaluate chest X-ray images for categorization and diagnosis. The proposed model performed better than the other deep learning models and achieved the accuracy is 0.9721. Combining GRU superior sequential learning capabilities with CNN experience in feature extraction led to this increased accuracy. Future studies may employ sophisticated hyperparameters tuning method to enhance the model performance and efficacy, and reinforcement learning strategies may be examined to further optimize model performance.

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