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ADVANCED DISEASE DETECTION USING HYBRID CNN WITH LSTM AND GRU MODELS: A DEEP LEARNING APPROACH

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ABSTRACT

The area of medicine has seen a tremendous transformation as a result of the incorporation of cutting-edge technologies like machine learning. This study combines a hybrid structure combining Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks and Gated Recurrent Unit (GRU), to enhance the accuracy of sickness analysis and remedy prediction. The aim is to leverage CNN for feature extraction from imaging information and LSTM for temporal pattern reputation in time-series patient data and GRU for sequential data. Medical datasets for illnesses which include lung cancer, brain tumors, pneumonia, tuberculosis, skin cancer and breast cancers had been used, with a pre-processing that protectes records balancing, normalization, and augmentation. The CNN-LSTM version validated superior overall performance as compared to CNN-GRU and traditional models, with full-size enhancements in accuracy throughout more than one illnesses. Key findings indicate that the CNN-LSTM model achieves an accuracy of an average 99.2% and 98.6% for CNN-GRU, highlighting its efficacy in complicated diagnostic eventualities. This research underscores the ability of mixing CNN with LSTM and GRU for advanced disease diagnosis, presenting a scalable and powerful method for healthcare packages. The study's effects advocate better avenues for future findings, together with actual-time medical diagnostics and the enlargement of the dataset to include extra numerous clinical conditions.

Keywords: *Healthcare, Convolutional Neural Network, Disease Diagnosis, Long Short-Term Memory, Gated Recurrent Unit*

1. INTRODUCTION

Disease diagnosis and treatment hold a prominent position in the medical community, since they are often regarded as indispensable to patient care and health management. Since it directly affects the efficiency of therapies and the course of therapy, an accurate diagnosis is essential [1]. While clinical assessments, medical histories, and laboratory testing have always played a major role in diagnosis, the quick development of medical technologies has greatly increased the scope of diagnostic possibilities. Disease diagnosis especially in those illnesses, which may progress rapidly or those that require timely treatment for risks' mitigation is crucial towards better patient outcomes. Due to advances in diagnostics that have happened recently through genetic testing, biomarkers, advanced imaging that has been evolved clinicians may now diagnose illnesses more accurately and in early stages [2]. With the advent of these technologies, therapy paradigms have been completely changed as a result of the increased understanding of patient-specific characteristics and illness causes. Advanced diagnostic methods have also contributed to emergence of such concepts as individualized medicine based on the fact that specific therapies' effectiveness and their side effects decrease when compared to the fact that they adjust them according to the patient's characteristics. In addition, since various diagnostic methods have been merged together, a broader perspective of the patients' health has been achieved, as well as enhanced disease control and improved decision-making concerning the patients' conditions [3]. Higher diagnostic accuracy of diseases is enabling enhanced therapy besides improved technologies offering new therapy strategies. As knowledge in the medical field increases, prevention and initial treatment of the illness gain significance due to the fact that people wish to treat their diseases before they get serious. The long term expectation of this preventive approach would reduce health care cost and at the same time improve the general wellbeing of patients on the overall [4]. Therefore, innovations in the accuracy of testing, the available treatments and care for enhanced quality of health are effecting a revolution in the diagnostics and cure of ailments.

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Current approaches have numerous important issues and limits that have been brought to light by recent studies in medical imaging and illness diagnosis. This is the case because the effectiveness of the ML models is significantly hinged on the availability and quality of data, and where there is lack of it, or it is of poor quality, then the career is impaired [5]. Many medical datasets are small and heterogeneous, and this means that models trained on them may overlearn and thus be less accurate. However, despite of methods like data augmentation, transfer learning and others these problems have not been solved yet especially the problem of missing and imbalanced data. The vast computation cost and huge amount of computations needed to train DL models are other challenges [6]. Some of the complicated architectures like the CNN and the RNN might be costly to train for many healthcare facility for these reasons. In addition to this, even when pretrained models such as VGG16 and VGG19 have better accuracy, fine-tuning is often required to transform them into models suitable for specific medical fields. This process may be time-consuming and may involve a lot of work and research [7]. Furthermore, there are two problems with DL models; extractability or interpretability of the feature maps. Some of these models work in what is called the 'cockpit of darkness,' and doctors are unable to verify the recommendations that the algorithms in the models present to them or comprehend the workings of the models. This opacity may make it less easy to apply AI technology in healthcare environments in which explainability and trust are critical [8]. Moreover, current approaches face challenges in integrate sources of information where full understanding of patient health is affected such as merging genomes, electronic health records with imaging information. To overcome these limitations there is a need for more research plus increased use of creativity and innovation in the development of methodologies for improving the interconnection between several data sets, reducing the computational intensity of the process, enhancing the interpretability of models, and optimizing the quality of available data [9].

The proposed approach incorporates CNN networks [10], with LSTM and GRU to enhance the identification of illness and its treatment against the concerns that were highlighted earlier in related literatures. Due to the ability of our approach to leverage learned features and enhance performance with relatively limited medical databases — the pre-trained CNN models that we employ for transfer learning. Most of these models have been trained, not on sample sets but on fairly large data sets which enable one get over the set problem of small, unbalanced data sets. Temporal dependencies in sequential medical data are challenged through LSTM and GRU networks which brings dynamism in the knowledge of patient health and accurate prediction of diseases occurrence in time. This combination strategy not only increases the interpretability and integration of varied data sources, but also improves the model's ability to generalize from limited data. As a result, our approach overcomes significant shortcomings in existing approaches and advances medical imaging and AI-driven healthcare by offering a more thorough, accurate, and effective framework for illness diagnosis and therapy.

The key contributions are as follows:

- ❖ The suggested models are ensured to handle unbalanced, real-world datasets well by collecting six varied datasets encompassing lung cancer, brain tumors, pneumonia, tuberculosis, breast cancer, and skin cancer.
- ❖ Medical data has sequential and temporal dependencies that are captured by LSTM and GRU models, whereas CNN is utilized for robust feature extraction from medical pictures.
- ❖ To give predictions in real time, a scalable web-based interface is designed that integrates with clinical systems to detect diseases.
- ❖ Numerous tests show that CNN-LSTM and CNN-GRU models outperform state-of-the-art techniques, with CNN-LSTM obtaining better metrics in the majority of cases.

The structure of the study is as follows: The section I starts with the introduction of the study. Related work of the paper presents in the Section II followed by problem statement in section III. The methodology of the paper in section IV with its result in section V. The study concludes with the conclusion and future work in section VI.

2. RELATED WORKS

Ray and Chaudhuri, [11] examine the applications of data mining (DM) and artificial intelligence (AI) in the healthcare sector, with a focus on ML and its use of classification and predictive analytics. They demonstrate how the creation of strong early detection services and health solutions is facilitated by the use of DM as a potent tool for pattern recognition and knowledge retrieval from large datasets. The analysis highlights the essential role that timing plays in clinical decision-making and highlights the significance of precise prediction models for a range of disorders. The authors have discussed and over-viewed the various techniques, the algorithms and performance indices used in the different predictive healthcare models by analyzing large number of articles. They explain recent ambiguities and demonstrate the fluctuations in the prediction results even when handling the same data as they introduce the opposition between statistical analysis and ML. The analysis also points out to the fact that although the current prediction models hold promise, new methods need to be fine tuned continually. The limitation of the study, is that, though it proceeds through very careful scrutiny indeed, it remains true that the accuracy of different models can vary at the end of the process, implying that one cannot yet speak of an ideal model.

Mansour et al., [12] introduce a completely innovative solution that gathers data through the Internet of Things and wearables and sensors and applies artificial intelligence for diabetes and heart disease diagnosis. These are collectively called phases, which entitle Data Collection phase, Data Cleaning phase, Data Categorization phase and Parametric Tuning phase. In order to enhance the diagnostic accuracy, therefore, the weights and biases belonging to a CLSTM model are fine-tuned using the CSO approach. It is also notable that the model performance is boosted through the application of the iForest method for outliers' elimination. During the validation process using health care data, the obtained CSO-CLSTM model provided the following high accuracy rates: 96. Diabetes was the commonest comorbidity with a prevalence of 16% and cardiac dysrhythmias had the highest prevalence of 97%. 26% for heart disease. Despite these findings the work has some limitations, the first of which is that while the authors have used the CSO-CLSTM model to classify the macroeconomic indicators, there might be variations in how the model performs on different datasets or in a real-world environment hence the need to fine-tune the model further. The effectiveness of the model is also dependent on the quality and quantity, and the variation of the data collected

Nazir et al., [13] look at how DL is improving gene editing, drug development, protein-protein interaction analysis, and early cancer diagnosis. DL is also altering healthcare. The study demonstrates how DL algorithms significantly enhance medical data processing, supporting treatment planning and diagnosis. Additionally, it looks at how combining medical records with AI might advance robotic surgery. The investigation of cutting-edge technologies for early illness diagnosis are among the important discoveries. In addition, the paper discusses XAI approaches like Grad CAM that promote openness and comprehension in AI decision-making processes, as well as FL and its ethical concerns for medical datasets. The report points out that despite these developments, there are still issues with integrating DL into healthcare, such as the need for more reliable AI model interpretability and data privacy concerns. Future studies, according to the scientists, ought to tackle these issues and look at further DL uses in medicine.

Khanna et al., [14] discuss for the first time the concept of the IoT and DL enabled Healthcare Disease Diagnosis model which enhance the healthcare early monitoring with the help of wearables, sensor technologies and the latest achievements in the field of IoT. It has been derived from ECG impulses biological that are fast and non-invasive diagnostic of CVD. The IoTDL-HDD model applies the AFO technique to enhance the extraction features from ECG data where BiLSTM is employed, as well as the improvement of the related hyperparameters. Subsequently, the ECG signals undergo an accurate classification through utilisation of a FDNN classifier. When applied to actual biological ECG data, the performance of the model was found to be very high accuracy. The study recognizes a limitation despite the encouraging results: its versatility to different kinds of populations or if the quality of the signal will always remain constant are other things which are yet to be investigated. Some limitations of the model include the likelihood of variations in the pattern of ECG signals in different people affecting the performance of the model.

Refaee and Shamsudheen, [15] propose a disease diagnosis model which incorporate DL with IoT technologies. The suggested model has multiple phases: Data extraction includes: (a) acquiring data from multiple Internet of Things wearables with sensors to collect medical data; (b) filtering out noise in the data collected; (c) using an iForest technique to detect outliers as it serves well known for its linear time complexity in addition to having relatively high accuracy; (d) a classification using PSO-DenseNet169 to improve the accuracy and optimize the parameters used in the data set. When the constructed model was checked alongside other techniques, it came out on heights with an accuracy level of 96% in both heart disease and thyroid illness. 16% and 97. 26%, respectively. A weakness of the research is that although the suggested model works well on certain datasets, the results when implemented on different types of medical data or on various real life situations may produce some other results, meaning that more testing in modification is required in this respect.

Ahmad et al., [16] address privacy and security issues in the management of healthcare data by presenting the OPPDL-DD model for the IoMT environment. Using an IoMT device to gather patient data, preparing the data for quality optimization, and using a Radix Tree structure to lower computing cost are all part of the concept. In order to provide safe data transmission and reconstruction in the cloud, the study used the EIG-RSO for data encryption. A hybrid model that combines CNN and GRU is used to diagnose the condition. Benchmark dataset simulations show that the OPPDL-DD model performs better than current approaches across a range of performance criteria. A limitation of the research, however, is that the efficiency and efficacy of the model might be highly dependent on the particular datasets and encryption methods employed; this means that it might not be applicable to all kinds of medical data or IoMT devices, necessitating additional testing in various real-world scenarios.

Hampiholi, [17] examine how AI is significantly improving healthcare, especially in the areas of early medical picture identification, diagnosis, and categorization. They tackle the problem of closing the semantic divide in picture classification that results from conventional ML methods that depend on laborious, low-level feature extraction. The paper highlights how Deep CNN can help with this problem by enhancing their capacity for picture categorization. The paper discusses a variety of AI models, such as CNNs, GAN, One-Class Learning Models, RNN, 3D and Multimodal Models, and others, that are used for autonomous illness identification and classification. These models are used in a variety of imaging modalities. Although the paper offers a thorough review of these models, one drawback is that the exact imaging modality and dataset employed might affect how effective these AI approaches are, which could have an impact on their generalizability and usefulness in a variety of clinical scenarios. To verify these models over a wider variety of situations and imaging modalities, more study is required.

Chen et al., [18] underline the important contributions that DL and AI have made to the detection and treatment of cancer. AI is a useful tool in many areas of cancer research because, in particular, DL is excellent at automated feature extraction and managing large, complicated datasets. The review discuss the involvement of AI in automating radiation therapy; drug discovery, planning and trials; molecular characterization of tumor related genes; cancer screening, diagnosis, staging, grading, prognosis and treatment. Understanding of fundamentals and numerous application of AI in cancer: issues and future prospects of AI and related papers. One constraint acknowledged despite the progress is the ability to form AI to solve difficulties related to its integration to clinical practice including data quality, model interpretability and variability of performance for different cancer types and different populations. In the current assessment, AI is revealed to have a risk of a profound overhaul of cancer treatment, yet more research and enhancement on the technology is needed before it could be fully implemented in clinical practice.

A review of various papers shows the use of AI, ML, and data mining in healthcare, notably for illness diagnosis and early detection. Techniques such as CLSTM, BiLSTM, and DL algorithms have been used on medical data with encouraging results, but problems remain. These include differences in model performance across datasets, privacy problems, data quality, and AI model interpretability. Furthermore, while AI has the potential to improve healthcare outcomes, its incorporation into clinical practice requires additional study and development. To solve these issues, we present CNN-LSTM and CNN-GRU models, which provide higher accuracy and flexibility for illness diagnosis and therapy predictions. These models are more adapted to dealing with complicated medical datasets and can reduce performance discrepancies, increasing the dependability and usability of AI in real-world healthcare settings.

3. PROBLEM STATEMENT

Current illness detection systems have considerable hurdles, such as data asymmetry, high processing costs, and inability to adequately address temporal relationships. Traditional methods, like as CNN, struggle with sequential data, limiting their usefulness in medical situations where patient history and time-series data are crucial. Furthermore, data imbalances in medical datasets frequently result in skewed outcomes, lowering the credibility of predictions [19]. The proposed solution overcomes these issues by combining CNN for image feature extraction with LSTM and GRU networks for processing time-series data. This hybrid technique improves both spatial and temporal pattern recognition, allowing for more accurate predictions across a range of medical problems. By balancing and enriching the datasets, the study guarantees that the models are trained on representative data, hence enhancing generalizability. The end result is a strong, efficient system with higher diagnostic accuracy than older approaches, particularly for disorders such as brain tumors, TB, and lung cancer.

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4. PROPOSED METHODOLOGY

The main goal of the study is to improve the results of the disease diagnosis and treatment using the latest DL approaches and optimization algorithms. The CNN with LSTM and GRU are used in the medical data. The process begins with grouping and loading more or less all kinds of medical information involving temporal patient charts and imaging. CNNs have been employed in feature extraction and pattern recognition of medical imaging whereas LSTM and GRU networks for processing time-series data. Several experiments are performed to confirm the effectiveness of the introduced approach and its benefits for increasing the effectiveness of illnesses' diagnosis and treatment in healthcare facilities. Figure 1. Illustrates the block Diagram of the study.

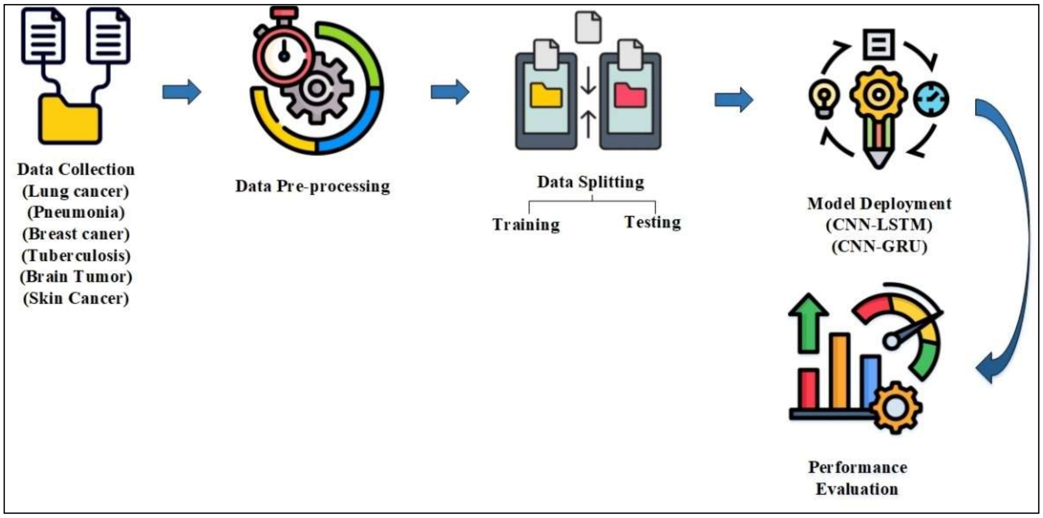

Figure 1: Block diagram of proposed model for the proposed study

The disease diagnosing through machine learning can be seen in the Fig. 1. It is essential to obtain various disease dataset and clean this data in the first instance. Following that, there is the CNN-LSTM and CNN-GRU model, which is evaluated in terms of its performance analysis. This pipeline is one of the examples of the systematic approach to apply deep learning, optimization and other complex methods to design an efficient and accurate system for disease diagnosis.

4.1. Data Collection

Medical pictures recorded in popular image formats (JPEG, PNG) or standard formats like DICOM are commonly found in image-based datasets, such as lung cancer, breast cancer, brain tumors, pneumonia, skin cancer and tuberculosis (TB), as seen in Fig. 2. However, as Fig. 3 illustrates, organized data on disorders of the heart, kidney, and liver is represented by CSV files that contain tabular data. These databases contain diagnostic results that correlate with patient-specific characteristics such age, sex, medical history, and laboratory test results. The dataset details utilized for study are displayed in Table I.

Table 1: Classification of Report of Diseases

Diseases	Dataset type	No of classes	Total Instances
Lung cancer [20]	CT scan Chest X-ray	4	907
Pneumonia [21]	Chest X-ray	2	5216
Skin cancer [22]	Skin type	7	11638
Tuberculosis [23]	Chest Radiography	2	4200
Breast cancer [24]	Breast Histopathology	2	3098
Brain tumor [25]	MRI Images	8	12481

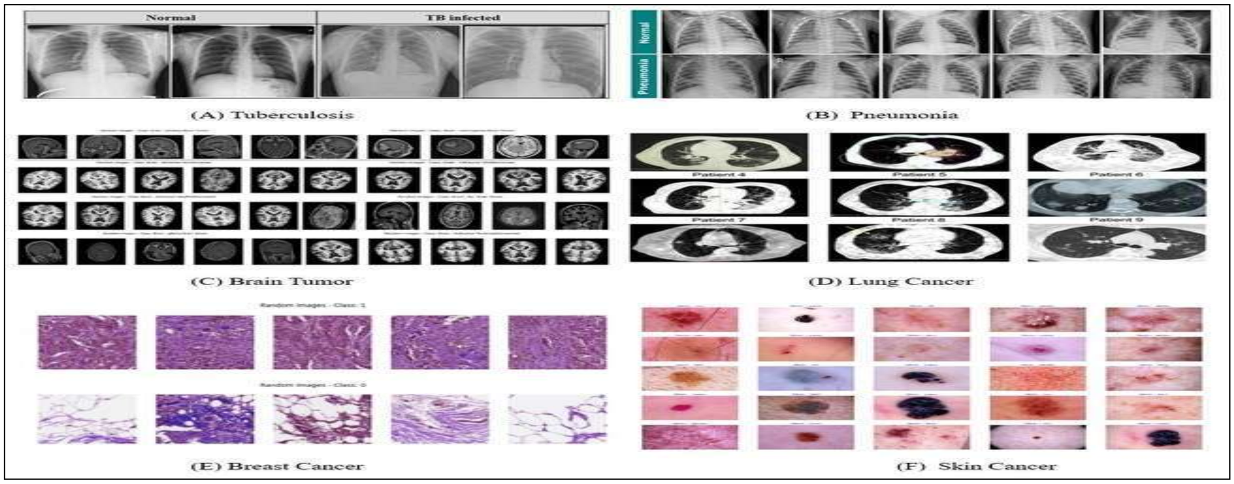

Figure 2: Samples images for image-based disease prediction

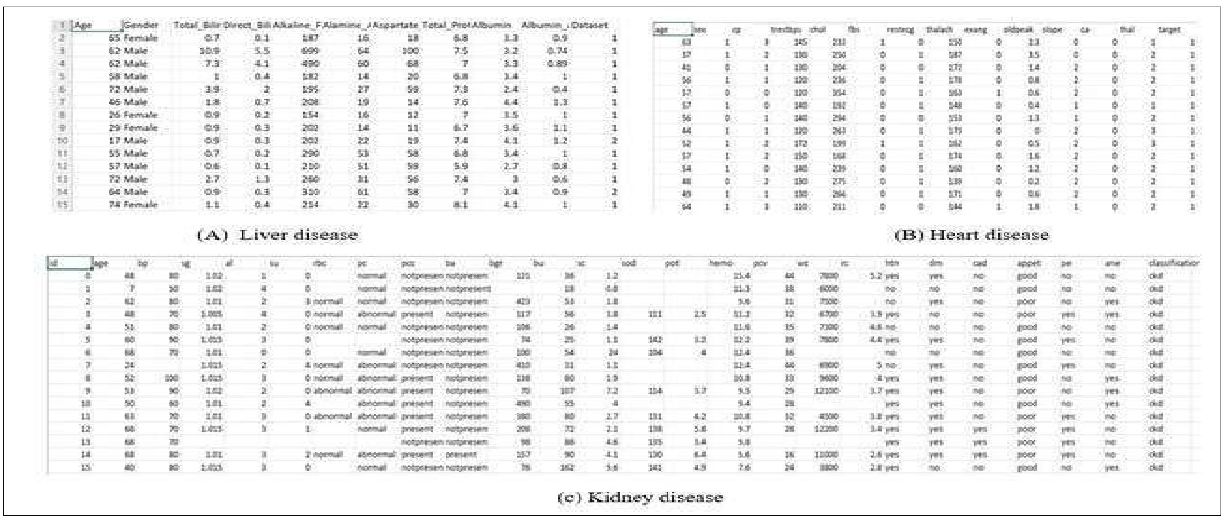

Figure 3: Samples images for CSV file-based disease prediction

4.2. Data Pre-processing

The data prepossessing step has a great impact on how effective using CNN with LSTM and GRU is in disease diagnosis, classification, and prediction. To construct a successful model, data pretreatment makes sure the input data is standardized, in a consistent format, and ready for training. Pre-processing data minimizes errors, handles missing values, and eliminates unnecessary information in order to ensure data quality for financial forecasting. To provide accurate and dependable predictions, it involves controlling outliers to avoid unbalanced analysis, encoding categorical variables for ML compatibility, and normalizing numerical data. All the six dataset goes through the data pre-processing steps.

4.2.1. Data Balancing

Data balancing a procedure for handling the imbalance of class characteristic in the dataset is by changing the class proportions in order to achieve accurate model and generalized. Its adopted tactics include an oversampling of all minority classes, an under sampling of all majority classes, and the development of synthetic data to the effect of achieving a more balanced dataset.

4.2.2. Data Normalizing

Data normalization is an operation that transforms the data elements into scales on the systems of ML capable of giving more reliable and accurate results in the models. This is typically accomplished through either feature scaling like that used in standardization that requires the data being altered that has a mean of zero and a standard deviation of one, or min-max scaling which is the scaling data between 0 and 1.

4.2.3. Data Sampling

By data sampling we mean a situation where a few aspects of a big data group are selected to be used to either infer more about the whole population, or

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address a particular research question. It could, however, employ straightforward random sampling, stratified sampling, or systematic sampling, depending on the target and research objectives.

4.2.4. Data Preparation

Data preparation includes but not limited to cleaning, transformation, and foregathering of raw data with the end in view of making it could be used for analysis or ML tasks. The data cleaning phase includes the processing of missing values and the identification of outliers. The feature engineering is performed by converting categorical variables to numerical format. The model is not the only factor that determines the quality and use of the analysis output; meticulous data preparation is the primary determinant of this.

4.2.5. Resizing the images

Lower the medical picture resolution for the models. To help with training, scale all image pixel values to the same measure. This will speed up convergence. Use augmentation techniques to make the model adaptable versus a limited number of instances of the provided data set and to artificially increase the size of the data set.

4.2.1. Data Visualization

The graphical depiction of data to facilitate information interpretation, analysis, and communication is known as data visualization. To illustrate patterns, trends, and linkages within datasets, visual components like charts, graphs, and maps are created.

4.3. Data Splitting

Splitting data entails separating a dataset into two subsets: a training set and a test set. One aspect that is critical is to be careful with the process of splitting the data in order to prevent any manipulation with the distribution of the dataset while maintaining their integrity during training and testing sets.

4.3.1. Training Set

The training is the large part of the dataset that teaches the model. The model tries to extract patterns, relations, and any features by using different learning algorithms and optimization techniques such as gradient descent, and stochastic gradient descent among others.

4.3.2. Testing Set

The test set is another portion of the data set for which the independent test set is created on a test set for grading the performance of the trained model. In response to the training on the training set, the model is validated on the testing set to determine how effectively it can apply new, unseen data. The test set provides information about the model's actual performance on real-time data and determines the likelihood of at least one overfitting issue.

4.4. Feature extraction and Disease Detection using CNN-LSTM

CNN feature extraction is governed by the architecture's hierarchical structure. The deeper layers integrate these components to identify more complex patterns, while the primary levels recorded the essential data. By learning these hierarchical features directly from the input, CNNs are able to automatically find pertinent information for a range of image analysis applications, including detecting the presence or absence of a tumor. Convolution, pooling, and non-linear activation functions are the three extraction methods used by CNN.

Convolutional layer: Feature extraction is the most frequent purpose of convolution layer, which is the widely applied sub-structure of CNN. As well, this unit is not the neutral one but its role is to detect patterns of data and give them instructions. The convolutional layers contain numerous convolutional filters which are then repeated and are the changing parameters at every iteration. Let $X^n \in R^{M^n \times N^n \times D^n}$ be our N-th convolutional layer's input and $F \in R^{m \times n \times d^n \times s}$ will be a rank four vector with each of kernels N-th layer undefined. The result of the N-th convolutional layer will be an order three vector with the notation $Y^k \in R^{M^n - m+1 \times N^n - n+1 \times s}$, with the components resulting from,

$$Y_{i^n, j^n, s} = \sum_{i=0}^{m} \sum_{j=0}^{n} \sum_{l=0}^{d^n} F_{i,j,d^n} \times X^n_{i^n, j^n, l} \quad (1)$$

If a geographic location satisfies the conditions $0 \leq i^n \leq m^n - m + 1$ and $0 \leq j^n \leq N^n - n + 1$, the Equation (10) must be performed for all $0 \leq s \leq S$. However, the CNNs convolutional layers are possibly a large number to permit the detection of the more salient visual patterns in the pictures. Padding with zeroes is one of the methods used to preserve the image's dimension when the image goes through the convolution layers. It ensures that you get the same result regardless of the image size.

Pooling layer: Take the N-class today, because it has changed to become one type of input of $m \times n$, have as its input $X^n \in R^{M^n \times N^n \times D^n}$. The other layers may turn out to be those without parameters, as since there are neither inputs nor outputs in those layers the variables can be learnt. The theory explained it by the help of a tensor of the third order which was actually created. The result is a tensor of

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order three indicated by $Y^n \in R^{M^{k+1} \times N^{n+1} \times D^{n+1}}$,were

$$M^{n+1} = \frac{M^n}{m}, N^{n+1} = \frac{N^n}{n}, D^{n+1} = D^n \quad (2)$$

On the other hand, pooling does not simply add up the parameters for each channel but globally distributes the parameters X^n across all the channels. There are several ways in which pooling structures can be formed, with the average pooling being the most dominant and followed by pooling through the maximum as the median being the most popular. leading to results that followed a formula

$$y_{i^n, j^n, d} = \max_{0 \le i \le m, 0 \le j \le n} x^n_{i^n \times m + i, j^n \times n + j, d} \quad (3)$$

Where, $0 \le i^n \le M^n, 0 \le j^n \le N^n$ and $0 \le d \le D^n$. Using pooling layers to lower the size of the output tensor while retaining the most significant features that were found makes sense.

Fully connected layer: This can be easily applied to the core fully connected layer in most cases with the required amendments. Running y_j will be computed for each run and compared to the real y_j saved as the loss function. In this situation, we believe that using the sigmoid function.

$$y_j = \frac{e^{x_j}}{1+e^{x_j}}, \quad x_j \in R \quad (4)$$

This will include not only the depth of the background but the right balance in this counter position as well. The fly-over photograph may convey a character's emotions of the presence or absence of a tumor represented by the expression$y_j \in (0,1)$.

It is dependent on the parameters of the default node network being set to zero by default. For instance, ReLU and Batch normalization are the two fundamental connectors which existed earlier and therefore, they are the ones required to enhance the performances of these networks. The definition of the ReLU function is

$$y_{i,j,d} = max\left(0, x^n_{i,j,d}\right) \quad (5)$$

Batch normalization makes neural networks faster and more stable by rescaling and recentering after each iteration. This is accomplished by attempting to convey only the essential elements for the categorization with $0 \le i \le M^n, 0 \le j \le N^n$ and $0 \le d \le D^n$.

Long Short-Term Memory Networks

LSTMs, are a type of neural networks that perform recurrent nature and are the most feasible solutions to a wide range of unpredictable problems. In using the gates that direct the flow of data in the right way, it is deployed to operate as a short-term fix for the memory problem. Three gates are used to alter the LSTM's long-term memory, which stores the cell state. These gates function as filters of this kind, and the next sections detail how they do so.

Input Gate: With the old being in the hidden state and the new being a fresh input signal, this gate goes ahead and selects which of the new data ought to be used to update the LSTM cell state. People take pleasure in learning about the LSTM input gate operation principle given in eqns. (12-14)

$$i_{0_t} = \sigma(W_i . [h_{t-1}, X_t] + b_i) \quad (8)$$

$$\tilde{C}_{0_t} = \tanh\,(W_i . [h_{t-1}, X_t] + b_i) \quad (9)$$

$$C_{0_t} = f_t C_{t-1} + i_t \tilde{C}_{0_t} \quad (10)$$

Where, W_i is weight matrix, b_i is input gates, C_{0_t} is memory information and $\tilde{C}_{0_t}$ is tanh.

Forget Gate: The gate is required to identify buzzwords as well as fresh input data that should be directly involved into the whole cell state. The principles of operation of the output gate in equation (15) are listed below.

$$f_{0_t} = \sigma(W_f . [h_{t-1}, X_t] + b_f) \quad (11)$$

Where, W_f is the weighted matrix, b_f is offsets and σ is the sigmoid curve.

Output Gate: The output gate calculates the most recent concealed state based on the most recent cellular state, the priority of those, and the current data input.in equation (17). The resulting gate concept in equation (16) is shown in this equation.

$$O_{0_t} = \sigma(W_0 . [h_{t-1}, X_t] + b_0) \quad (12)$$

$$h_t = O_{0_t} \tanh\,(C_{0_t}) \quad (13)$$

Where, W_0 describe the weighted matrices for the output gate.

$$b_0 = \text{Bias of LSTM} \quad (14)$$

The CNN model can handle a single image and convert its input pixels into a vector representation. Each input image in this case is subjected to the CNN Model, and the result is then supplied to the LSTM as one time step. On the basis of deep features retrieved with CNN and LSTM network, a deep model is suggested. The completely connected layers are where the deep characteristics are extracted. The LSTM layer receives the deep characteristics that were retrieved as input. Additional soft max layer and classification layer were utilized to finish this completely linked layer. It was already decided to change the deep network parameters for the present inquiry. As a result, the deep features derived from the available samples have already been compiled. Fig. 4 The CNN-LSTM's design is displayed as follows with its flowchart in Fig. 5.

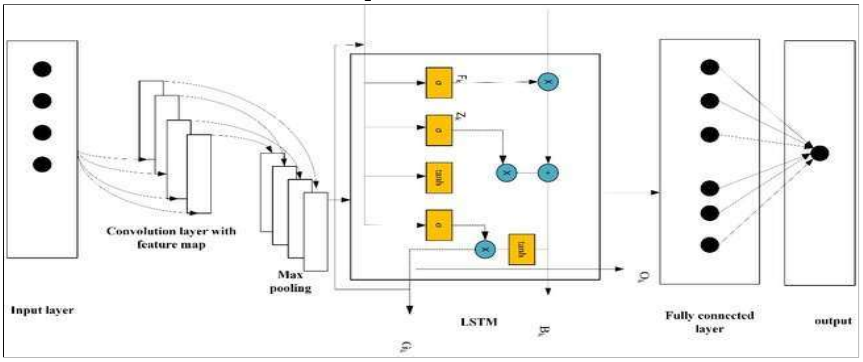

Figure 4: CNN-LSTM Architecture

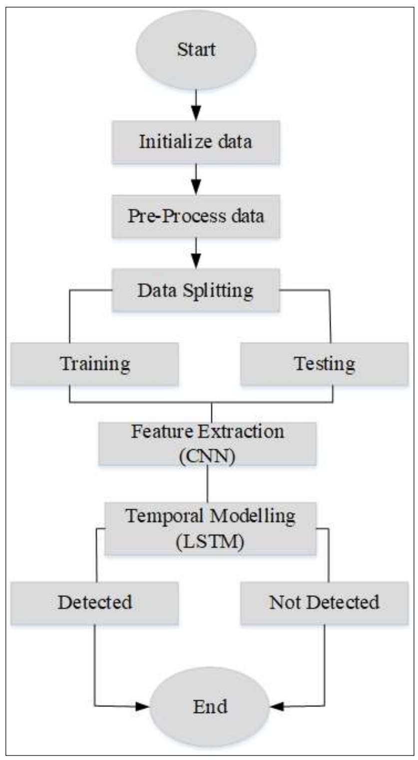

Figure 5: CNN-LSTM Flowchart

In the proposed study, the hybrid CNN-LSTM technique is crucial in improving illness diagnosis and therapy prediction. CNN are used because of their outstanding capacity to handle and interpret complicated picture data, such as medical scans, allowing for exact detection of disease patterns. The CNN's feature extraction capabilities guarantee that crucial visual information is recorded, which helps to accurately classify medical problems. LSTM networks, on the other hand, are designed to deal with time-series data such as patient history, treatment records, and the evolution of medical disorders over time. LSTMs are very good at understanding temporal relationships, which are critical for forecasting illness outcomes and developing individualized treatment plans. By learning from history and present patient data, LSTM networks increase the model's prediction capability, allowing for more educated and proactive medical care decisions. The combination of CNN and LSTM leverages the capabilities of both models, resulting in a complete framework that

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improves diagnostic accuracy. This hybrid strategy not only enhances illness identification accuracy but also makes it easier to build more effective treatment strategies, resulting in better healthcare outcomes across a wide range of medical diseases.

4.5. Feature extraction and Disease Detection using CNN-LSTM

The GRU model was most widely used in recurrent neural networks to solve the gradients vanishing problem RNN. GRUs have three major gates and an inner cell state, making them more efficient than LSTMs. Data is safely maintained within the GRU. The reset gate simply conveys prior knowledge, but the update gate provides both previous and future information. The current memory gate employs a reset gate to retain and maintain data from the system's previous state. The input modulation gate has zero-mean features and allows for the insertion of nonlinearity. The following equations (1) and (2) define the fundamental GRU of rest and the updated gates' mathematical formulation:

$$U_t = \sigma\,(X_t.Z_{xu} + F_{t-1}.Z_{hu} + d_u) \quad (15)$$

$$V_t = \sigma\,(X_t.Z_{xv} + F_{t-1}.Z_{hv} + d_v) \quad (16)$$

where Z_{xu} and Z_{xv} present weight parameters, while the d_v , $d_u$are biased. Fig. 6 represents the CNN-GRU model.

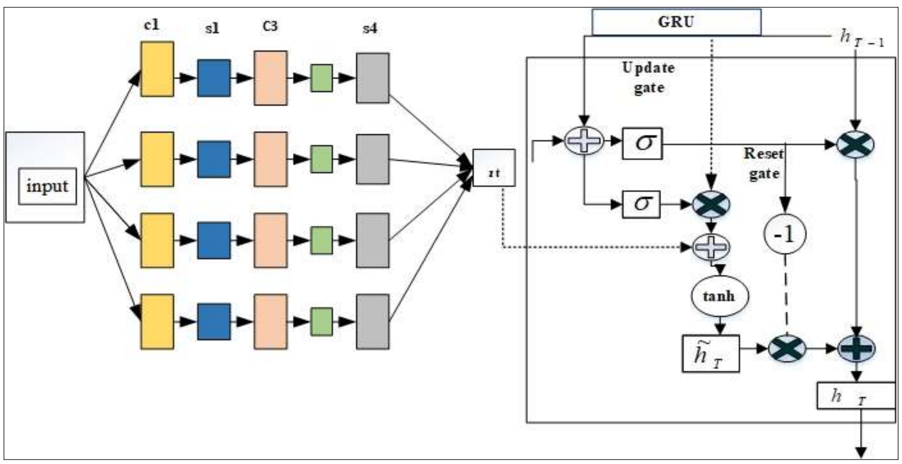

Figure 6: CNN-GRU Architecture

The CNN-GRU model combines a GRU for processing sequential medical data with the ability of CNN to extract features from complicated medical images. In order to extract features from high-dimensional data, such as X-ray, MRI, and CT scans, CNN is essential. With the help of automatically learning pertinent qualities including edges, textures, and patterns that match disease signs, it can help diagnose a variety of illnesses, including tuberculosis and pneumonia. GRU, a more straightforward LSTM variant with fewer parameters and an easier-to-understand design, is skilled at managing sequential dependencies in time-series data. GRU employs gating methods to manage data flow and efficiently identify both transient and permanent relationships in medical data. The benefit of GRU over LSTM is its computational efficiency, which makes it appropriate for applications like continuous monitoring and wearable health devices where real-time data processing is necessary. GRU is a good fit for real-time, resource-constrained environments because it processes temporal data such as patient history, symptom progression, and treatment records. However, it may not be as good as LSTM at capturing more complex dependencies. When combined with CNN, GRU improves disease prediction.

The Flowchart of the CNN-GRU is given in Fig. 7.

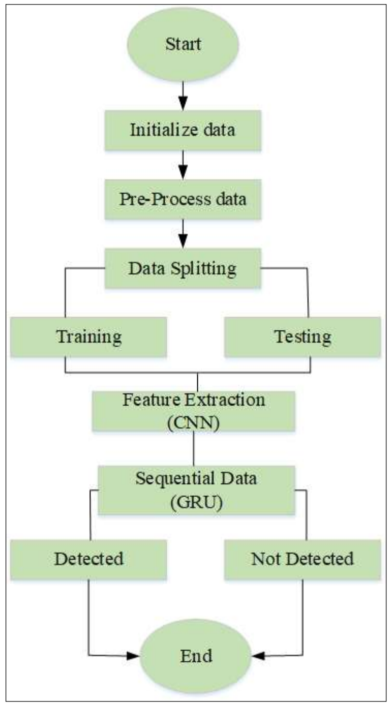

Figure 7: CNN-GRU Flowchart

5. RESULT AND DISCUSSION

The evaluation of the performance of the developed models encompassed several critical factors. Accuracy, the main performance metric, was computed as each model's percentage of total true predictions. This metric provided an overall assessment of the models' predictive capabilities. The overall result of the CNN-LSTM and CNN-GRU, comparison of the proposed with different method is also given in this section.

5.1. Result of CNN-LSTM

The training and testing accuracy and loss of the pneumonia, skin cancer, brain tumor, lung cancer, tuberculosis and breast cancer in CNN-LSTM model is given below in the fig. 8, 9, 10, 11, 12 and 13.

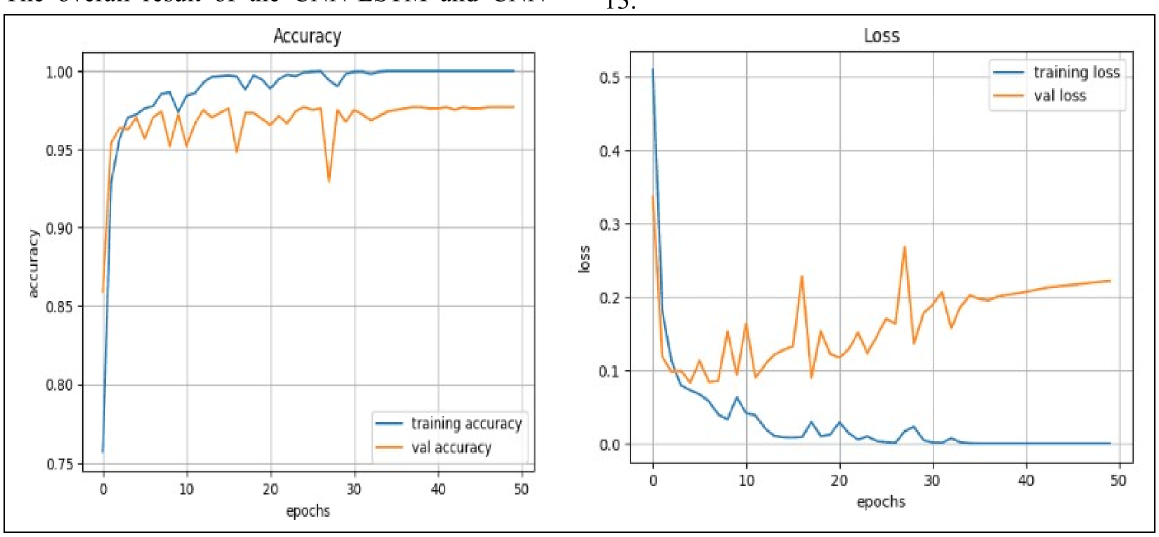

Figure 8: Results of Pneumonia with CNN-LSTM

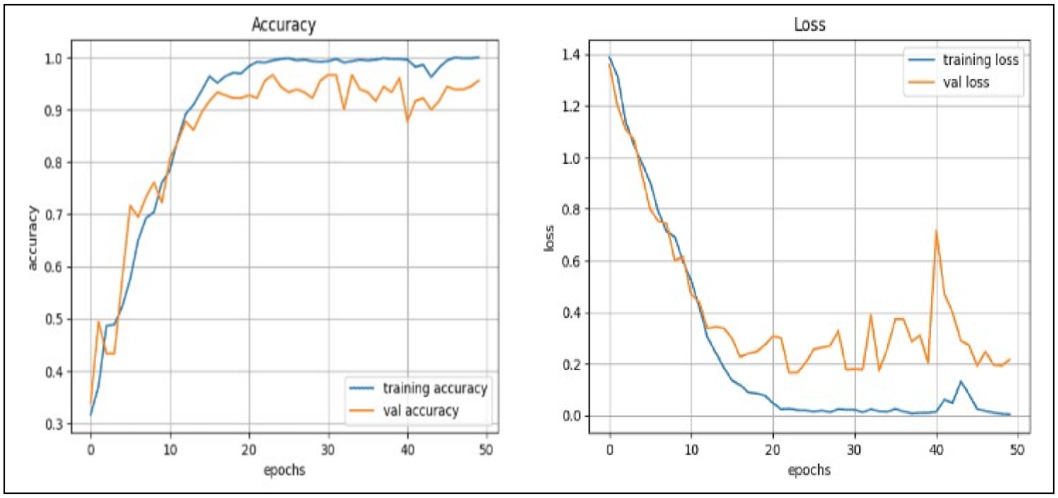

Figure 9: Results of Lung Cancer with CNN-LSTM

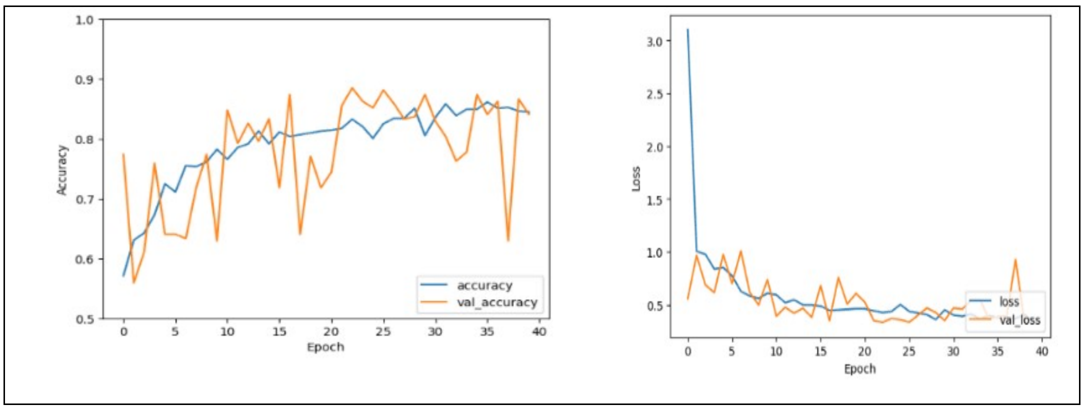

Figure 10: Results of Breast Cancer with CNN-LSTM

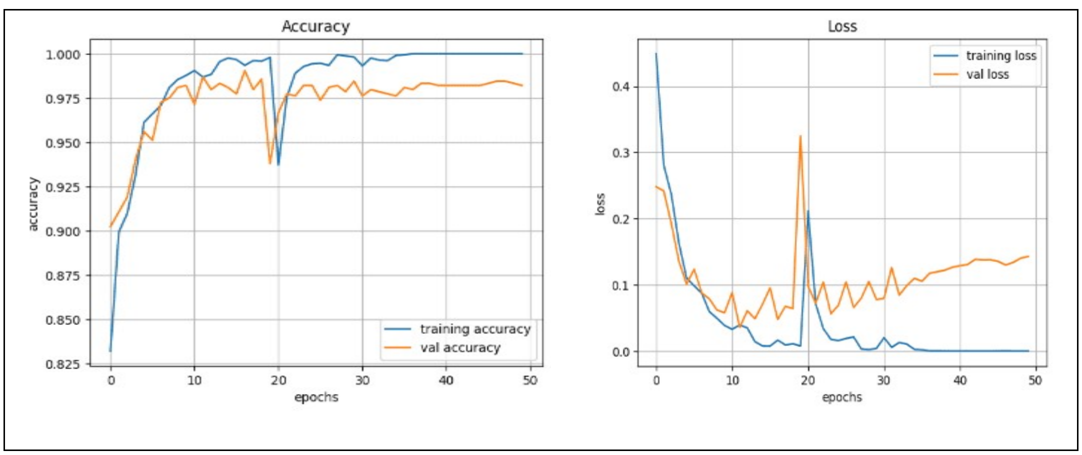

Figure 11: Results of Tuberculosis with CNN-LSTM

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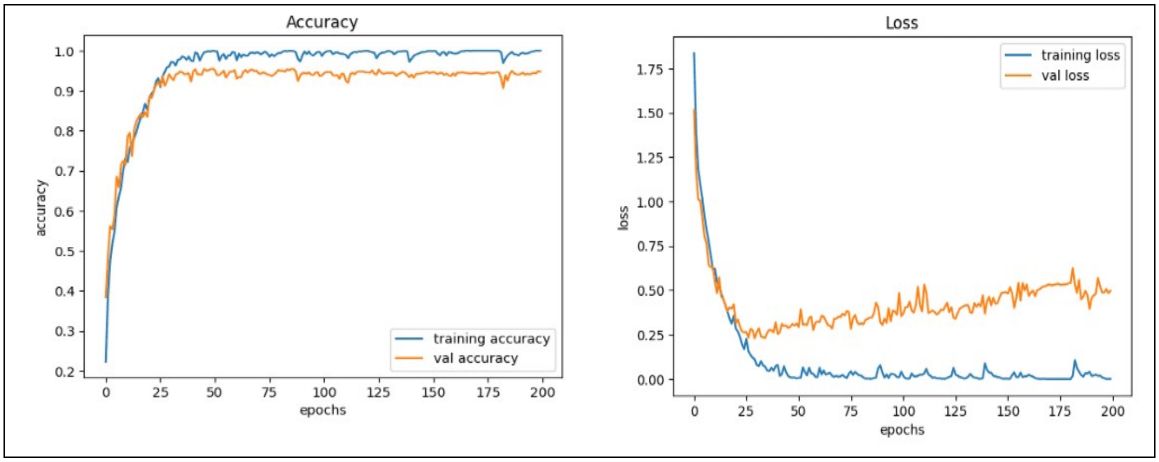

Figure 12: Results of Brain Tumor with CNN-LSTM

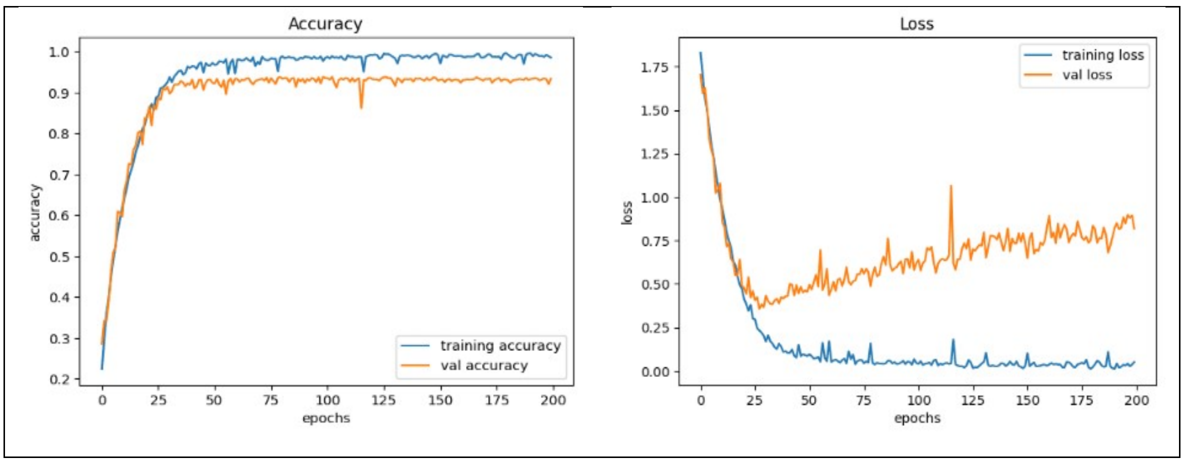

Figure 13: Results of skin Cancer with CNN-LSTM

5.2. Result of CNN-GRU

The training and testing accuracy and loss of the pneumonia, skin cancer, brain tumor, lung cancer, tuberculosis and breast cancer for the CNN-GRU model is given below in the fig. 14, 15, 16, 17, 18 and 19.

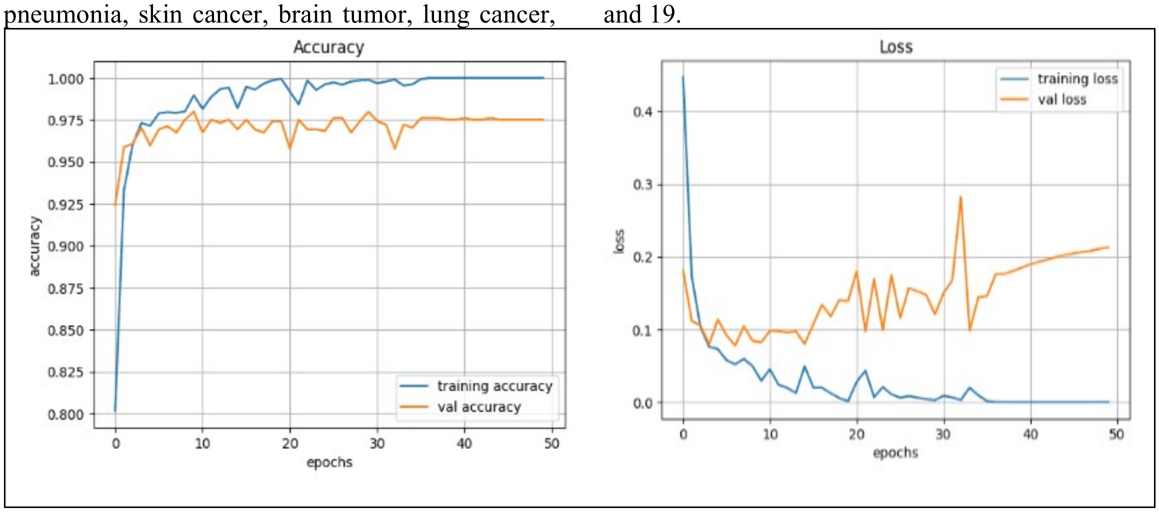

Figure 14: Results of Pneumonia with CNN-GRU

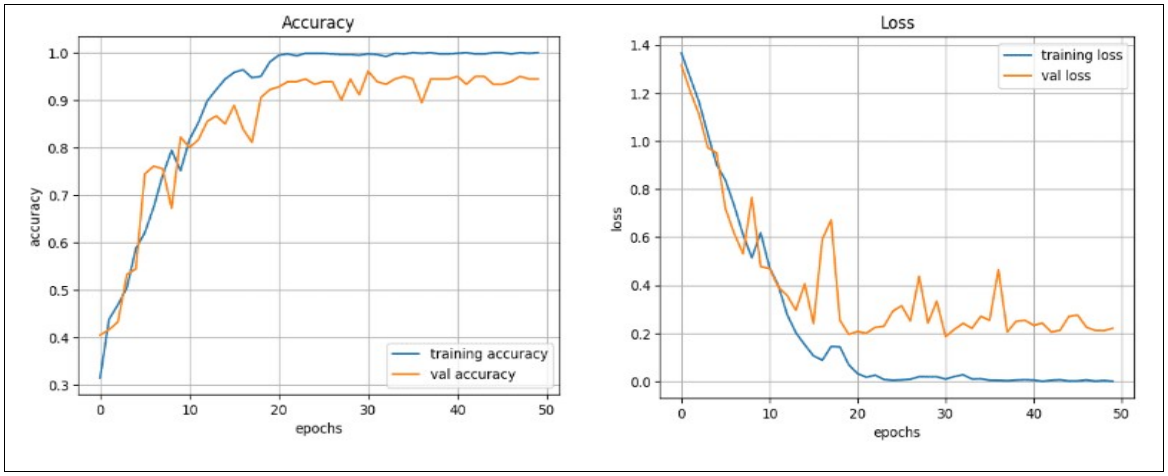

Figure 15: Results of Lung Cancer with CNN-GRU

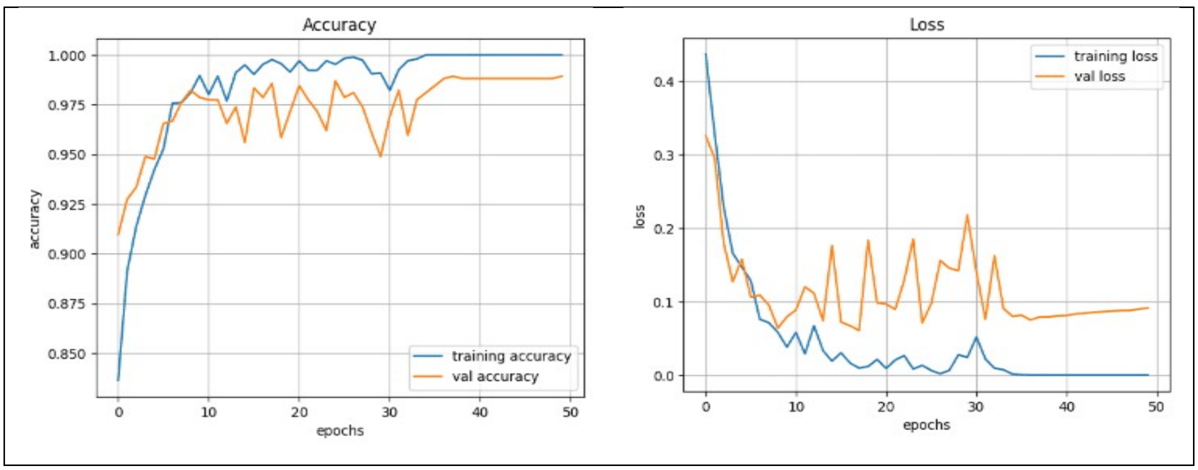

Figure 16: Results of Tuberculosis detection with CNN-GRU model

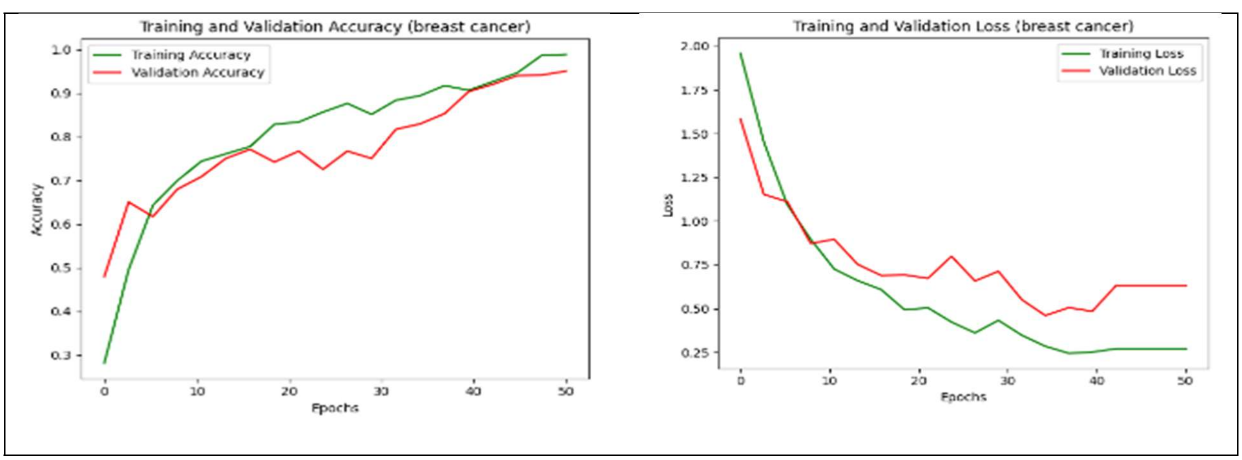

Figure 17: Results of breast cancer with CNN-GRU

5) Brain Tumor:

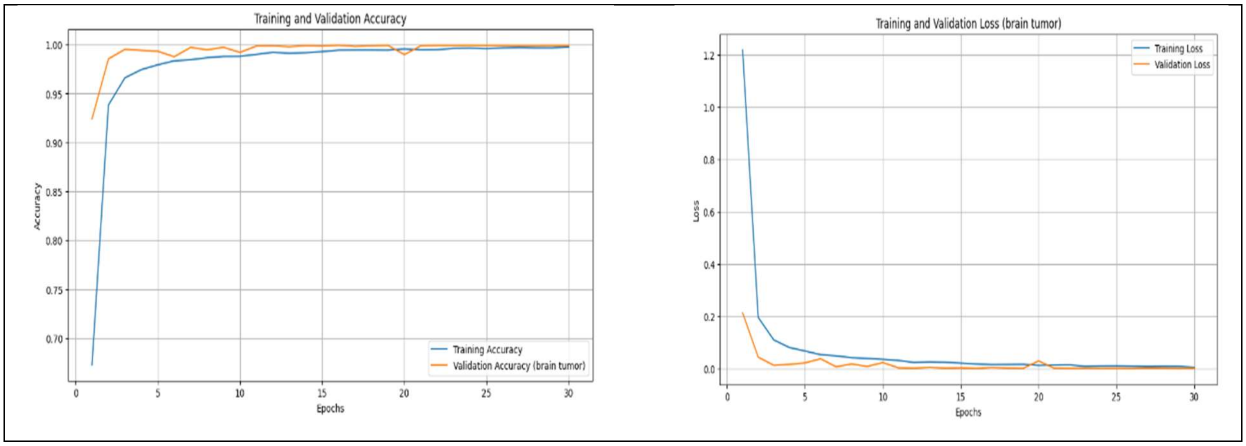

Figure 18: Results of brain tumor with CNN-GRU

6) Skin cancer:

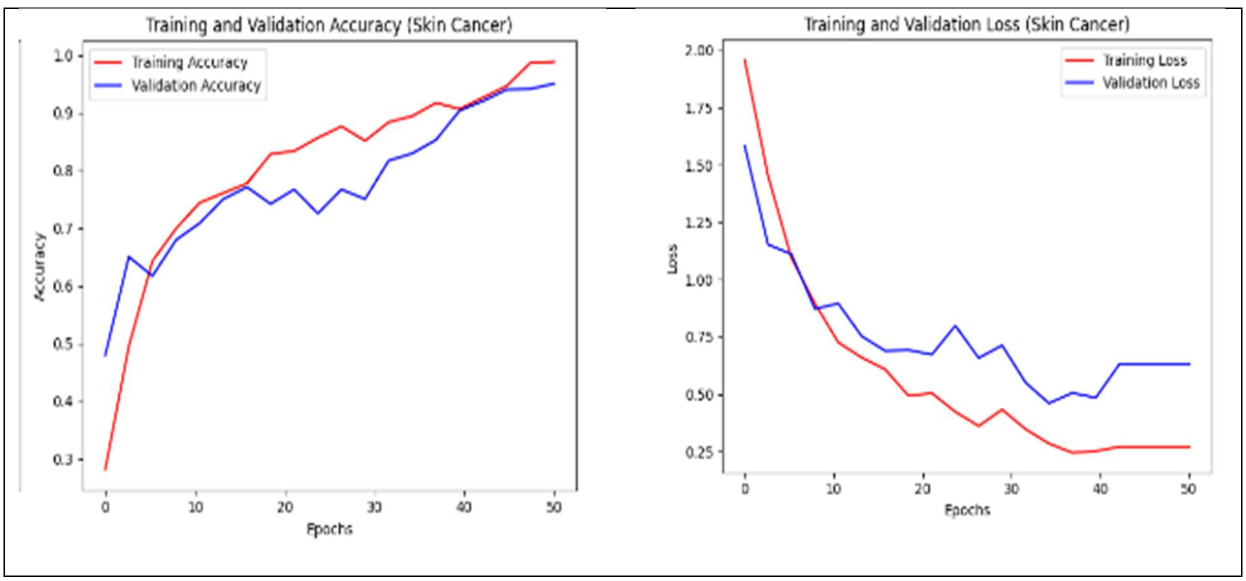

Figure 19: Results of skin cancer with CNN-GRU

5.3. Application Results

This will be considered the online application's outcome, which contains the particular illnesses, their early signs and precautions, as well as preventative measures and necessary activities. These diseases are accompanied by visuals, such as lung cancer, pneumonia, tuberculosis, skin cancer, brain tumor, and breast cancer, and data linguistic diseases, such as liver disease, heart disease, and kidney disease, will be delivered via CSV files or reports, as shown in Fig. 20.

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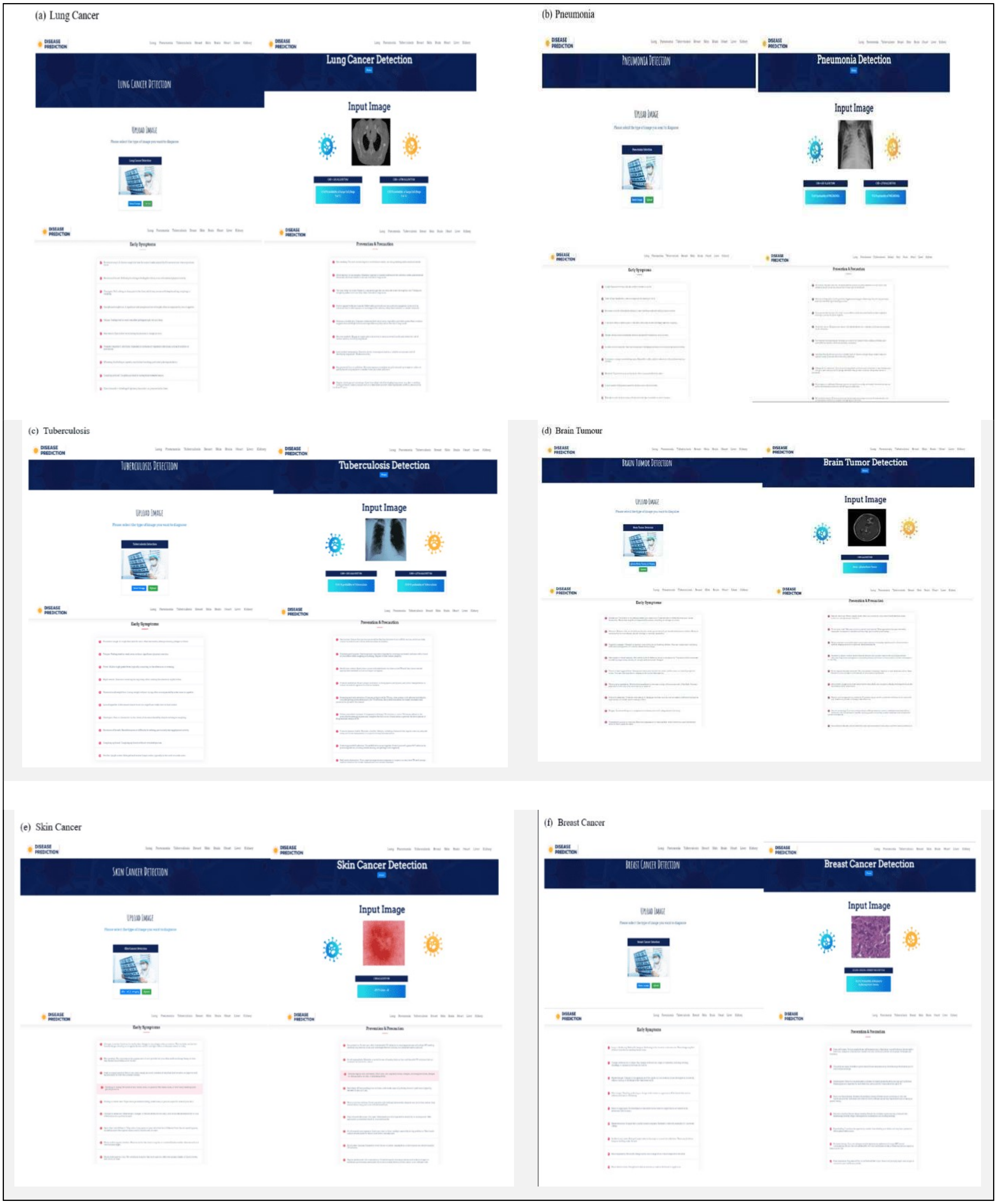

Figure. 20: Web application predicated Results for diseases.

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Table 2: Comparison table of the Proposed CNN-LSTM and CNN-GRU

Disease	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Pneumonia	CNN-LSTM	96.5	94.2	95.5	94.8
	CNN-GRU	94.8	93.5	92.1	92.8
Lung Cancer	CNN-LSTM	97.2	95.8	96.1	95.9
	CNN-GRU	95.6	94.2	93.7	93.9
Breast Cancer	CNN-LSTM	98.1	97.3	97.8	97.5
	CNN-GRU	96.5	95.9	95.2	95.5
Tuberculosis	CNN-LSTM	98.6	97.9	98.2	98.0
	CNN-GRU	97.4	96.3	96.8	96.5
Brain Tumor	CNN-LSTM	99.2	98.4	98.7	98.5
	CNN-GRU	98.1	97.2	97.4	97.3
Skin Cancer	CNN-LSTM	99	98.3	98.1	97.6
	CNN-GRU	97	96.4	96.1	96

The accuracy, precision, recall, and F1-score measures are used in this table II to compare the performance of two DL models, CNN-LSTM and CNN-GRU, across a number of diseases. For all diseases combined, CNN-LSTM performs better than CNN-GRU. In illnesses like pneumonia, lung cancer, and skin cancer, where CNN-LSTM exhibits a superior balance between precision, recall, and F1-score, the changes are most apparent. Both models perform remarkably well for diseases such as TB and brain tumors, but CNN-LSTM still has a little advantage. According to this, CNN-LSTM may provide better prediction performance in medical image-based disease diagnosis, even though both architectures are successful.

Table 3: Performance Comparison of the propsoed method with different methods

Methods	Disease	Accuracy	Precision	Recall	F1 score
CNN [26]	Heart disease	87.74	86.47	84.12	85
CNN-LSTM [27]	Brain tumor	84.96	96.2	76.5	85.2
SVM [28]	Lungs cancer	81.84	81.84	95	90.01
LSTM [14]	Skin disease	85.79	88	86.80	87.4
Proposed CNN-LSTM	Breast cancer	98.1	97.3	97.8	97.5
	Tuberculosis	98.6	97.9	98.2	98.0
	Lung cancer	97.2	95.8	96.1	95.9
	Brain tumors	99.2	98.4	98.7	98.5
	Pneumonia	96.5	94.2	95.5	94.8
	Skin cancer	99	98.3	98.1	97.6

The suggested method, CNN, LSTM, CNN-LSTM, SVM and proposed method are the techniques whose performance is compared in the table III based on four metrics: F1 score, accuracy, precision, recall, and recall. With a solid F1 score of 95.8%, the suggested technique exceeds all others with the greatest accuracy of 98.8%. Other approaches, such as LSTM and LSTM-CNN, have lower F1 scores and lack overall balance and consistency, although having strong areas like LSTM high accuracy (96.2%) and CNN-LSTM high recall (95%). The suggested approach of CNN-LSTM shows exceptional efficacy and dependability in attaining balanced precision-recall trade-offs and high accuracy.

The Fig 21. compares the performance of proposed CNN-LSTM-based methods with existing techniques for various diseases across four metrics: accuracy, precision, recall, and F1 score. The proposed models generally demonstrate higher or comparable performance, particularly for breast cancer, lung cancer, and other conditions, highlighting their effectiveness over traditional approaches like CNN, SVM, and LSTM.

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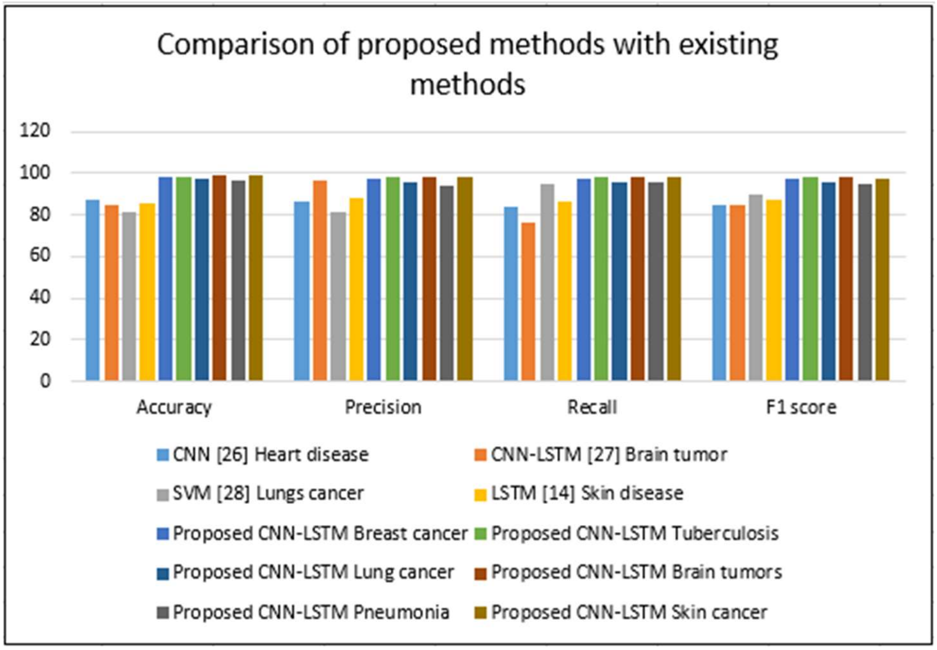

Figure 21. Comparison of proposed method with Existing methods

5.4. Discussion

The article describes a novel technique to illness detection that combines CNN with LSTM and GRU networks. The hybrid models use CNN to extract features from medical pictures and LSTM/GRU for temporal sequence modeling. This hybrid technique efficiently overcomes the constraints of CNN or classical models by collecting both spatial and temporal patterns, allowing for a more comprehensive examination of patient data. The study uses a broad dataset including six main illnesses to verify that the models are resilient and generalizable across different medical situations. The use of web-based prediction tools underlines the research's practical application by providing real-time illness detection capabilities in clinical settings. CNN-LSTM surpasses CNN-GRU in capturing long-term dependencies, making it the preferable model for more complex medical applications. This work emphasizes the need of mixing deep learning models to increase diagnosis accuracy, therefore establishing a new benchmark for AI-powered illness detection systems in healthcare.

6. CONCLUSION AND FUTURE WORKS

An considerable improvement in the precision and efficacy of illness diagnostic systems is demonstrated by the suggested study. Through the integration of CNNs for image analysis, LSTM and GRU for temporal data processing, the study obtains improved performance metrics in terms of metrics, among other assessment criteria. The fact that the suggested strategy is more efficient than the current one for solving intricate challenges in the sphere of healthcare can be studied in the example of the given article. As it can be seen from the results, the model improves not only the reliability of the diagnostic procedures but also the dependability of the therapeutical recommendations. Such an adopted approach has the potential to change the clinical decision-making and timely diagnosis of diseases that are fundamental to the patient's condition, both in terms of quality and speed. The study also underscores how synthetic intelligence models are changing current healthcare as it is a perfect start for future developments of medical diagnosis.

The attempt at including more diverse medical conditions and imaging techniques will be the focus of future work which uses the promising results of the current study to enhance the model's applicability across the board. Additionally, adoption of Explainable AI (XAI) techniques can enable deeper insights into the decision-making modules improving on the models interpretability and applicability in clinical environments. Two of these are: Another approach is applying Federated Learning (FL) frameworks to allow the training of a model in many health facilities without sharing patients' information. Further research may look at

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the adaptation of the model in real-time operational within health care environments, its effectiveness and viability in light of real-world, ever-changing health care environments. To enhance the understanding of the approach to the patient's needs and requirements and generate the basis for constructing a more elaborate diagnostic system, the model's approchability to recent advances in a technologically advanced health care setting, including wearables and the Internet of Medical Things (IoMT) will also be discussed. These developments will strengthen the model's position as a means of improving patient care and making the most use of healthcare resources.

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Conflict of interest

Corresponding author Nayan Jadhav contributed to the conceptualization, methodology, data collection, and analysis. Nayan Jadhav has responsible for writing the original draft, with contributions from first author Dr. Aziz Makandar they also provided supervision and paper administration. Contributed to the review, and editing of the manuscript. And provided critical feedback also revision of the manuscript. All authors have read and approved the final manuscript.

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Statement of informed consent

The authors declare that informed consent was obtained from all individual participants included in the study. Participants were informed about the study's objectives, procedures, potential risks, and benefits. Their participation was voluntary, and they had the right to withdraw at any time without any repercussions. All procedures were conducted in accordance with the ethical standards of the institutional research. Declaration and its later amendments or comparable ethical standards.

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