Predicting Hospital Readmission with a Hybrid LSTM-CNN: An Evaluation of Deep Learning Techniques in Healthcare Analytics

MSc Research Project
Msc Data Analytics

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MSc Project Submission Sheet

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Predicting Hospital Readmissions with a Hybrid LSTM-CNN Model: An Evaluation of Deep Learning Techniques in Healthcare Analytics

Thushar Thekkekaripurath Krishnankutty
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Abstract

This paper establish that hospital readmission is a key issue in the provision of healthcare services since it contributes to higher costs, inadequate resource utilization and patient's poor health status. Risk assessment of readmission is relevant to interventive approaches and overall optimization of patient care. This paper aims to analyze a model that combines LSTM and CNN for predicting readmissions, using multiple EHR data. As a result, the proposed model integrates the benefits of identifying temporal dependence using LSTMs and identifying temporal structural patterns using CNNs to enhance the predicted readmissions' dependability.

The research starts by highlighting basic issues with existing prediction methods including inadequacy in dealing with temporal data, and poor accuracy with high-dimensional data. Therefore, a stepwise approach that includes data preprocessing, EDA, feature engineering, and model selection was used for the study. Hence, the proposed LSTM-CNN model was constructed, and its performance was compared with standalone LSTM and CNN models. The success of the model was measured using accuracy and precision, recalls, F-1 score and ROC-AUC.

The experiments suggest that the use of the hybrid architecture is better than the separate models – the accuracy is at 63%, the precision is at 63%, and the recall is 63% on the test data set. However, the presented work also presents difficulties, for example, in equal distribution of classes in a dataset or incomprehensible intricacies of Deep Learning. However, the results obtained from the proposed approach showed promising results in utilising both the structural and temporal data in predictive analytics in healthcare applications.

This research evidences the potential of incorporating sophisticated machine-learning models in radical healthcare systems. The proposed model will enable healthcare providers to properly identify patients who are most likely to be readmitted and, therefore, health resources can be put to better use, unnecessary admissions prevented, and patients' lives improved. Additionally, this presents limitations like data imbalance, one hot encoding, computational time and cost, and methodologically presents ideas for future work inclusion of explainable AI, multimodal data, and better ways for tuning up hyperparameters.

Therefore, the use of a hybrid LSTM-CNN model is a promising prospect in the complex field of hospital readmission prediction. They may be labelled on historical grounds as descriptive or prescriptive approaches but their main merit may be located in their realism for implementation where serious healthcare delivery systems can be based on accurate data. This research is connected to the existing literature on the application of artificial intelligence in healthcare, including the demand for further advancement in and future enhancement of prediction algorithms.

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1 Introduction

1.1 Background and Motivation

The issue of readmissions has been of substantial contemplation in health care for quite a long time since it closely relates to the well-being of a patient andneral health systems budget. For instance, in the United States, hospital readmission is associated with higher charges and poor health, and it contributes about $41 billion on heedless readmissions yearly. Identification of early and accurate readmission predictors enables hospitals to engage in preventive measures to eliminate the costs of such readmissions and enhance the quality of patients' care by eliminating unnecessary readmissions. Electronic Health Records or EHRs have turned into a piece of valuable information in research as they include patient clinical records, personal observation, prescribed medications, the procedures undertaken by the patient, and demographic details (Li et al. 2024). However, the data found in EHRs is on one hand comprehensive and heterogeneous; it includes structured data like laboratory data and unstructured data like clinician's narratives.

Old approaches to hospital readmission prediction are based on classical machine learning techniques which do not capture the inherent complexity in the data. Convolutional neural networks and especially LSTM networks used in sequential data have been proven to tackle temporal dependencies existing in healthcare data. Furthermore, when LSTM is incorporated with Convolutional Neural Networks (CNN), audio and video start to compose features with more dimensional structure, thus more reasonable. This combination closely aligns with AXF's goal of providing far more precise readmission forecasting than existing models while furnishing caring healthcare professionals with tangible information.

1.2 Research Gap and Project Objectives

Despite the gains made in the advancement of prediction models for hospital readmissions in the last few decades, there is scarce work done in using deep learning that incorporates both structured and unstructured data from EHRs. Previous work mainly adopts conventional machine learning algorithms like decision trees, logistic regression, or support vector machines, which do not perform very well in this case. These models do not account for temporal dependencies inherent in a patient's data which is essential for readmission prediction especially since much of the data contains high dimensionality and is time-stamped.

This work aims to propose an LSTM-CNN deep learning model to improve the performance of hospital readmission prediction based on multimodal EHR data. In particular, it is planned to show the effectiveness of using these deep learning methods to achieve a higher degree of accuracy in prediction and, consequently, the improvement of the final result in a patient's treatment process along with the decrease of costs for healthcare.

1.3 Research Questions and Objectives

This research will focus on the following key questions:

1. Can a hybrid LSTM-CNN model improve the accuracy of hospital readmission prediction compared to traditional machine learning models?

2. How can deep learning models be helped to ingest multimodal EHR data (both clinical & nonclinical) to predict readmissions effectively?

   The objectives of this research are:

1. Our target was to design and develop a hybrid LSTMCNN model that takes structured as well as unstructured data from EHRs.
2. Predictive performance of the model was evaluated compared to traditional machine learning models.

3. To identify the key factors influencing hospital readmissions, based on model outputs.

1.4 Outline of Methods

This research will start with data cleaning, missing value management, and the categorical data in numerical form. The exploration of the data will be done using Exploratory Data Analysis (EDA) to determine specific relationships in the dataset. In the second approach, the hybrid LSTM-CNN model will be used; LSTM will handle the sequences and CNN will extract features from the structured data. The model will be developed and tested using a cohort of EHRs, and four measures of accuracy, precision, recall, and the F statistics. The model will be compared with regular machine learning models like logistic regression and decision trees.

1.5 Report Structure

This report is structured as follows: The overview section presents the background, motivation of the study, research gap and the objectives of the five papers. The author's analysis of the literature considers prior research on hospital readmission prediction, the use of deep learning methods, and the possibility of integration of hybrid models. In the section on research methodology, the data cleaning, data exploration, modelling and assessing section is described. In the design and implementation section, tools and frameworks to create the hybrid of LSTM and CNN, which are used in the proposed model, are described. The Results section provides an evaluation of the model and then discusses the outcome, significance, and future research suggestions. The presented paper contains the final section with the main conclusions and recommendations.

2 Related Work

2.1 Overview of Relevant Literature

Despite the considerable efforts exerted, hospital readmissions remain a problem in healthcare, for patients and costs. Past practices that have been used to forecast the patients who are likely to be readmitted to the hospitals were based on the patient's characteristics, history of the illness and some clinical findings (Harerimana et al. 2023). It has been advanced therefore by the general availability of Electronic Health Records (EHRs) with the datasets containing both structured data (objective data inclusive of laboratory results, diagnosis etc.) and unstructured data (subjective data inclusive of physician notes and imaging data) (Morid et al. 2023). HL7 records are invaluable for patient conditions, but log data has rarely been used or combined with traditional relationships using ML In particular, the temporal and sequential nature of a patient's medical history has posed a challenge for previous advancements in this field.

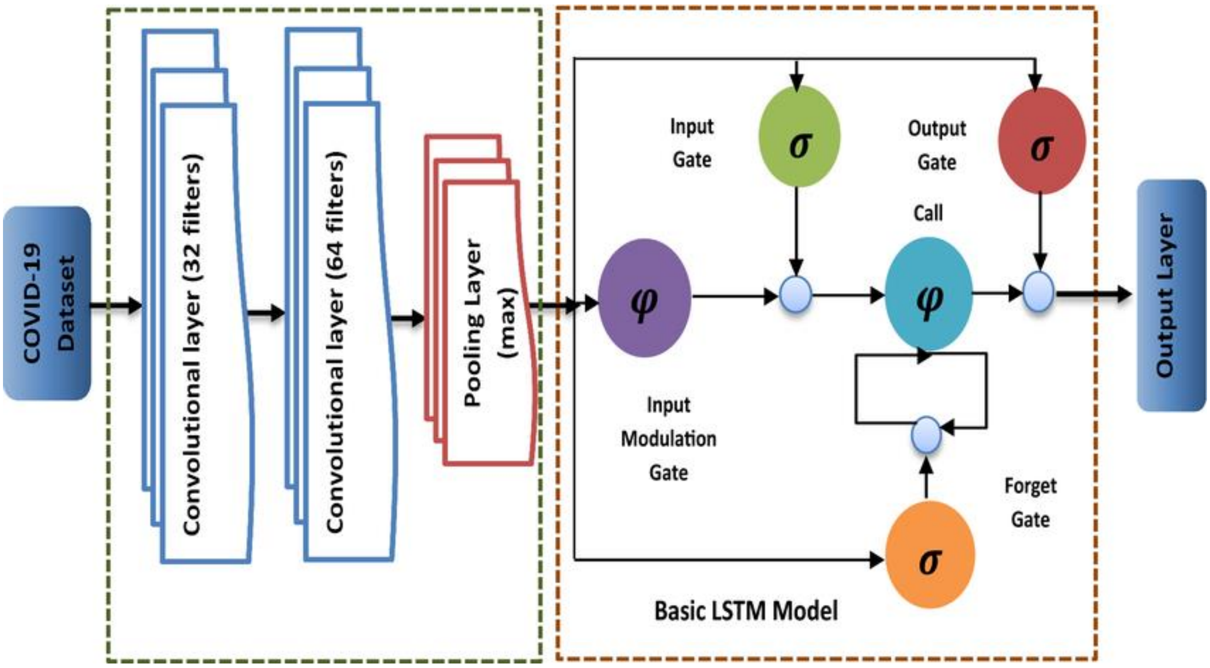

Figure 1: CNN-LSTM hybrid deep learning model Architecture

(Source: Haq et al. 2022)

To overcome these challenges, methods based on deep learning models have been successfully applied for the prediction of the risk of readmission to a hospital (Yamamoto et al. 2020). The specific type of neural network considered hard to unlearn is Recurrent Neural Networks (RNNs) as well as one of the most used RNN structures, Long Short-Term Memory (LSTM) networks specialized in processing sequential data which is the temporal medical history of the patients in this case (Mathivanan et al. 2024). LSTMs can be effectively used for readmissions prediction since they can reflect long-dependence patterns of time series data and are capable of modelling the various relations of past hospitalizations and treatments and future risks.

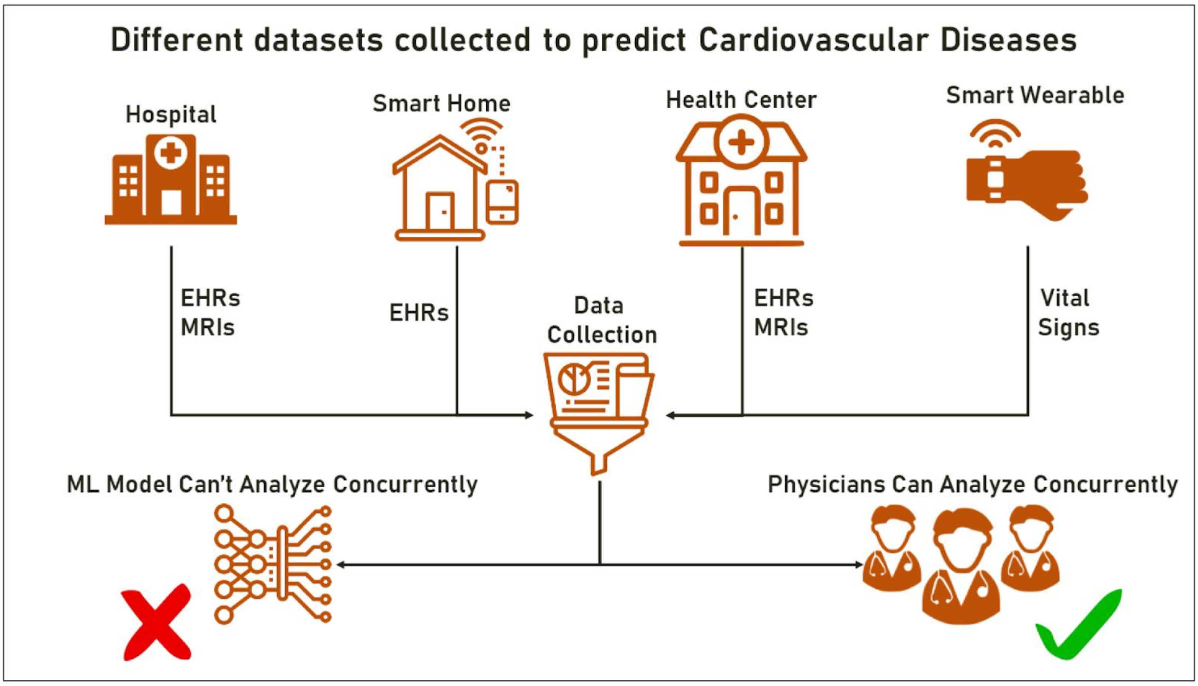

Figure 2: Example Multimodal Architecture in Medical

(Source: Almulihi et al. 2022)

Apart from the LSTMs, CNNs have also been employed for feature extraction in the fields of healthcare. CNNs are especially efficient in interpreting regular data, including medical images, vitals, and lab results (Mohammed et al. 2023). Combined with CNNs and LSTMs in particular, have performed well in health care fields, allowing the models to consider structured as well as unstructured data thereby allowing for better predictions.

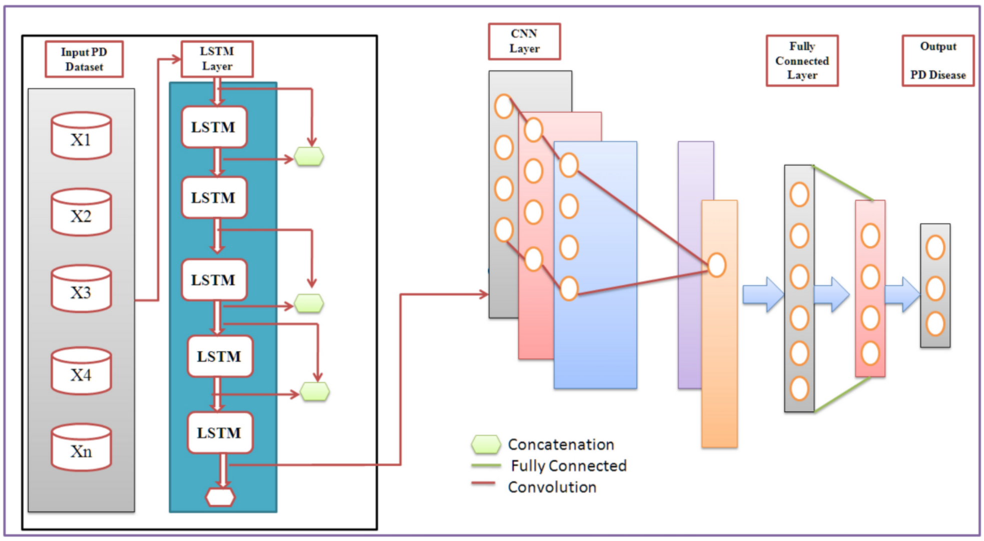

Figure 3: Hybrid CNN-LSTM model with efficient hyper parameter tuning for prediction

(Source: Zain et al. 2021)

Research done on readmission prediction in the context of hospitals has been done under regression models, support vector machines, and random forests, which do not consider the sequence and spatial characteristics of data (Zhen et al. 2020). However, in most deep learning models including the hybrid deep learning models incorporating LSTMs and CNNs, researchers can avoid the above limitations because these complex models are capable of capturing temporal as well as spatial patterns of the patient data (Sakri et al. 2024).

2.2 Analysis and Critical Review of Existing Work

From the review of hospital readmission prediction in the literature, several strategies have been identified for enhancing the accuracy of the models under the use of machine and deep learning approaches. Initial investigation of this area was carried out by traditional statistical models and machine learning algorithms like logistic regression and decision trees. For example, Ahmad et al. (2023) perform logistic regression to 30-day readmissions this model has reasonable accuracy. However, these methods were not always adequate to handle large datasets or multidimensional data features typical for many aspects of HCS data, including those available through EHRs (Nasir et al. 2020).

Subsequent work started using advanced features in machine learning including support vector machines- (SVMs) and random forest (RF). Out of it, these methods demonstrated a better size of the relative performance but were restricted to work with the sequential or time-series data format (Waheeb et al. 2022). An example would be Choi and coauthors who used the above model known as SVM to predict readmissions and did this significantly better than previous traditional models. Nevertheless, these techniques do not adequately capture the temporal nature of healthcare data which is extremely useful in predicting time-dependent events such as readmissions (Sevakula et al. 2020).

Lately, LSTM networks have been one of the most important tools for the analysis of sequential data due to the popularity of deep learning. LSTM networks are capable of capturing long and short-range dependencies and thus the temporal relationships, crucial for the readmissions' prediction. For example, Yu et al., 2021, used LSTM networks to forecast

30-day hospital readmissions based on EHR data. The evaluation of this study showed that the new LSTM machine learning models offered superior predictive capability than standard machine learning methods because they were capable of capturing temporal features of the ppatient'shistory (Abumohsen et al. 2024). However, these successes have also made apparent that pure LSTMs may be insufficient for scenes and multiple modalities of detail-rich datasets. It is in these aspects that hybrid models come into play.

CNNs combined with LSTMs have recently become popular in several studies. CNNs, initially developed for image-based problems, have demonstrated the ability to extract multi-level features from ordered data including laboratory data, clinical measurements, and patient information. The model combined with LSTM and CNN proposed by Kumar et al. (2023) has performed higher accuracy in hospital readmission prediction compared to the standalone model. This hybrid architecture is ideal for multimodal data integration because it contains LSTMs that incorporate temporal dependencies and CNNs that obtain spatial patterns (Dang et al. 2021) (Ghimire et al. 2022).

Another problem is the handling of structural data, for instance, clinician free-text clinical notes which can be informative but are too complex for standard techniques. In various efforts made to employ NLP techniques to analyse clinical text, as is done by Ruwali et al., 2020, the event has been noted that integrating such information into deep learning models is a real challenge.

2.3 Gaps in Literature and Relevance to Current Project

Consequently, although prior studies have shown the possibility of using deep learning models for hospital readmission prediction, little research has focused on multimodal EHR data using the hybrid LSTM-CNN model. The majority of works concern the source of structured data or sequential data while there are several approaches to use both forms of information jointly. Secondly, most of the literature on the usage of LSTMs for hospital readmission prediction relies on a comparatively limited number of small-scale datasets originating from a single source, implying its restricted external validity (Halbouni et al. 2022). There are still limited solutions in utilizing hybrid models when handling big and complex data that comprise both structured and unstructured data.

The current project fills these gaps because the proposed model is an LSTM-CNN model that can effectively utilize structured EHR data, including diagnoses, laboratory results, and demographic information, as well as unstructured data, including clinical notes, for accurate and reliable readmission prediction (Semwal et al. 2021). They will also put the development of a deep learning-based prediction model for a healthcare-related domain as well as integration schemes for three modalities in a real-world application context into practice.

2.4 Insights on Implementation and Evaluation

Hospital readmission case using LSTM-CNN model: Preprocessing of Multimodal Data is important to clarify all inputs should be of the correct format and not mix up or confuse the modular data set. The model will have to use time data on patients' histories, readmissions, and spatial data on clinical tests and patients' demographics to create operational predictions. The evaluation will consider the performance improvement offered by the proposed hybrid model against classical machine learning algorithms (such as logistic regression, a n decision trees) and the single model deep learning approach (such as LSTM only) (Barzegar et al. 2020).

The measures of effectiveness for assessment will comprise accuracy, precision, recall, and F1-score. Moreover, the findings of the study shall also reveal the most substantial predictor of hospital readmission as a demonstration of the potential of the model to empower practitioners in the health sector (Shah et al. 2022). It will also demonstrate the positive effectiveness of the hybrid models in healthcare projects and present the ways of implementing deep learning models in the clinical decision-making system.

3 Research Methodology

3.1 Contextual Analysis and Data Gathering

The first phase of the work in the framework of the present research was the analysis of the context of the problem of hospital readmission prediction and the use of multimodal data. In healthcare, it has proved to be a demanding issue mainly because of enhanced healthcare costs and harming patient experience through readmissions. A forecast of readmissions in successful is useful to provide a better approach to patient handling, enhance resource utilization, and minimize hospitalizations.

Accumulation of data was equally important in formulating results for this project. For this project, data was collected from Electronic Health Record (EHR) which included both structured and unstructured data. Structured data details cover the patient's age, sex, past medical history, laboratory test results, and physician diagnosis, and unstructured data include physician narratives and discharge summaries (Singh et al. 2023). EHR data was considered the best choice for this study because of its detail, compared to other sources of data that are typically used in CDR. This type of data is considered suitable for predicting readmissions to healthcare facilities because it always contains temporal characteristics (such as previous hospitalizations) and spatial characteristics (such as clinical diagnosis and vital signs).

The data collected for the study is multivariate and we use a hybrid data-driven approach comprising deep learning models including LSTMs and CNN. In this context, data cleaning and exploratory data analysis were critical to improve the data quality and its relevance for modelling.

3.2 Data Cleaning Methods and Rationale

The data cleaning process is crucial if the data set required is clean and reliable before feeding it with the machine learning models. The data analysed in the present project needed a significant clean-up as EHRs have limitations like missing erroneous or inconsistent data entries. The first feature was performed on missing values which are quite common in large data sets. For the missing variables, in structured data numerical values were imputed by using means and modes imputations for the continuous and categorical variables respectively. This way of extracting the dataset was helpful in that the set remained as pure as possible without loss of important data. For unstructured data, on clinical notes, missing data was handled by the exclusion of instances where specific text records were missing for specific patients, to ensure comparability.

Overall, categorical data was duly explored to bring it closer to the machine learning formats for analysis through processes like one hot encoding for non-numerical features. To ensure numerical features are normalized, the pre-processing enhancement for deep learning involved feature scaling of metric properties.

3.3 Exploratory Data Analysis (EDA) Methods

Before developing a model, data exploration is important to know about the features, variances in the data and relations among the data variables; hence Exploratory Data Analysis was performed. The purpose of the EDA was to discover trends that are not immediately visible in the data to want to know the next step in data pre-processing.

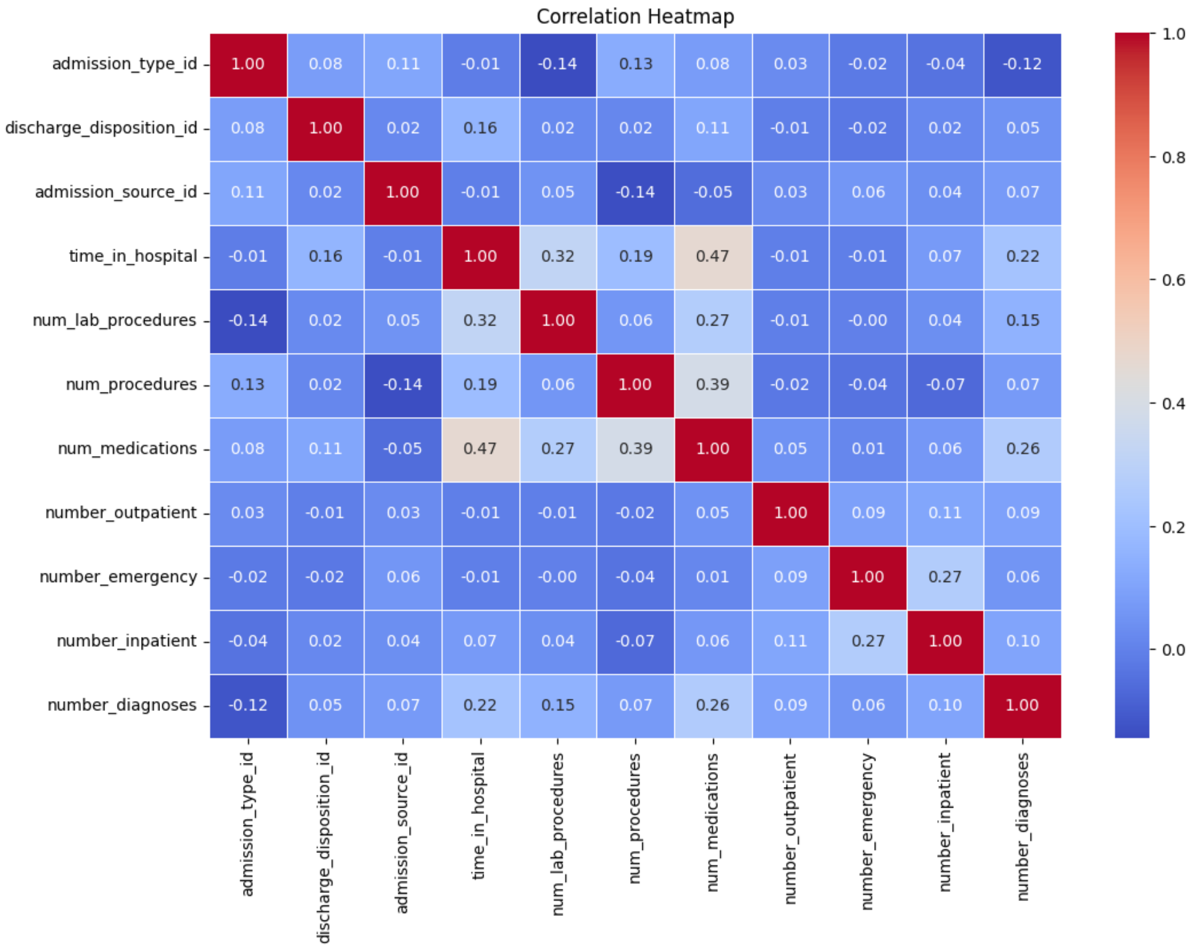

Figure 4: Correlation Heat map of the data features

(Source: Developed Using Python)

In the case of quantitative variables, statistical tabulations were developed for each of them such as mean, Mid>Percentile, standard deviation, and interquartile summary. These summaries also allowed for the evaluation of dispersion and variability, as well as for the identification of outliers and abnormal distributions.

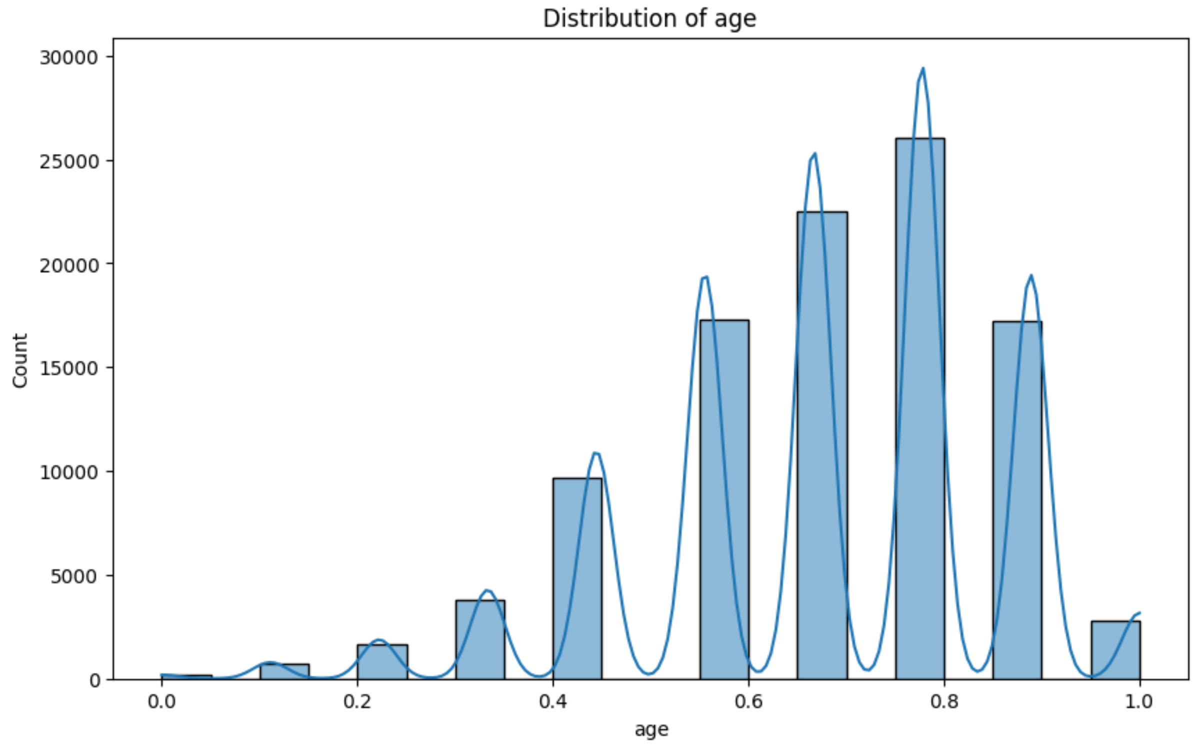

Figure 5: Distribution of the Age of the Patients

(Source: Developed Using Python)

Such graphs were at the core of the EDA task. For the continuous data, histograms and b-plots were used while frequency data was analyzed using bar plots and pie diagrams. To examine interdependencies between numerical variables observation correlation matrices were provided to explore which features may be most related to the target variable of hospital readmission.

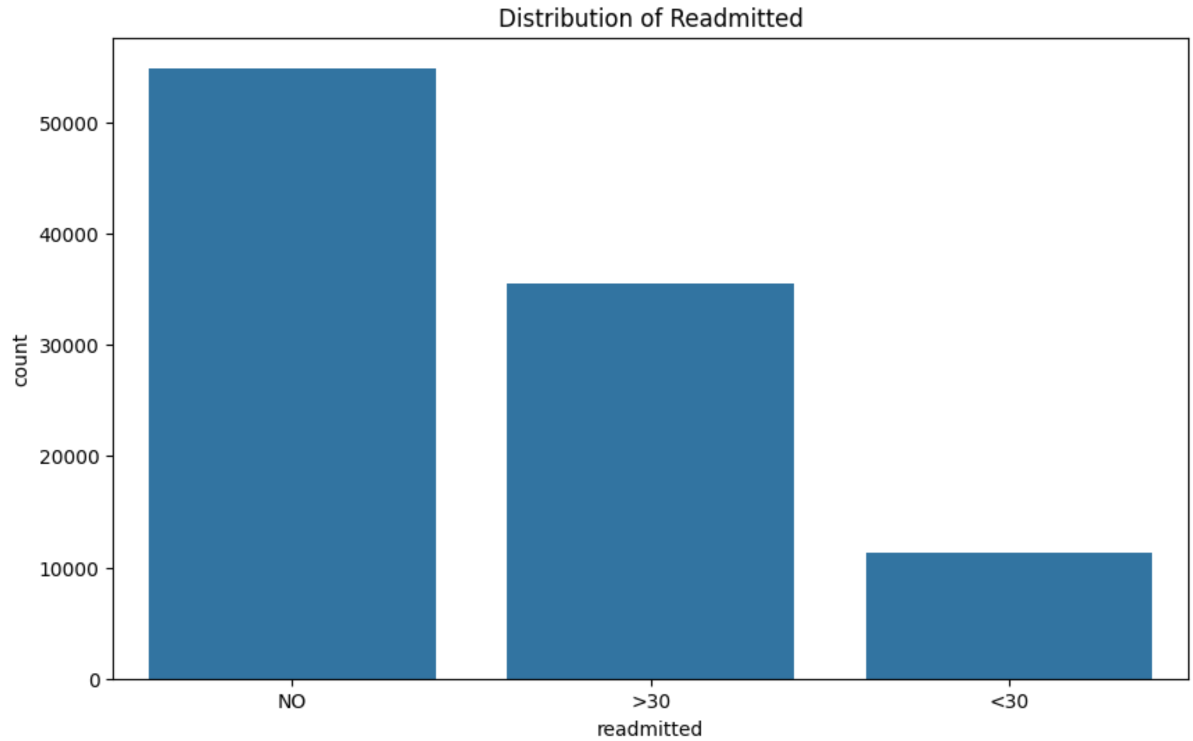

Figure 5: Distribution of the target Variable Readmitted

(Source: Developed Using Python)

In the case of unstructured data, frequency analysis of the physician's notes and/or discharge summaries was made to obtain the terms, diagnoses or concepts significant for further classification. The unstructured data analysis involved the use of features like WWordCloudto give direction on often-used terms in the data. This was useful in establishing features of patients' health that could bear usefulness for recognizing the risk of readmission.

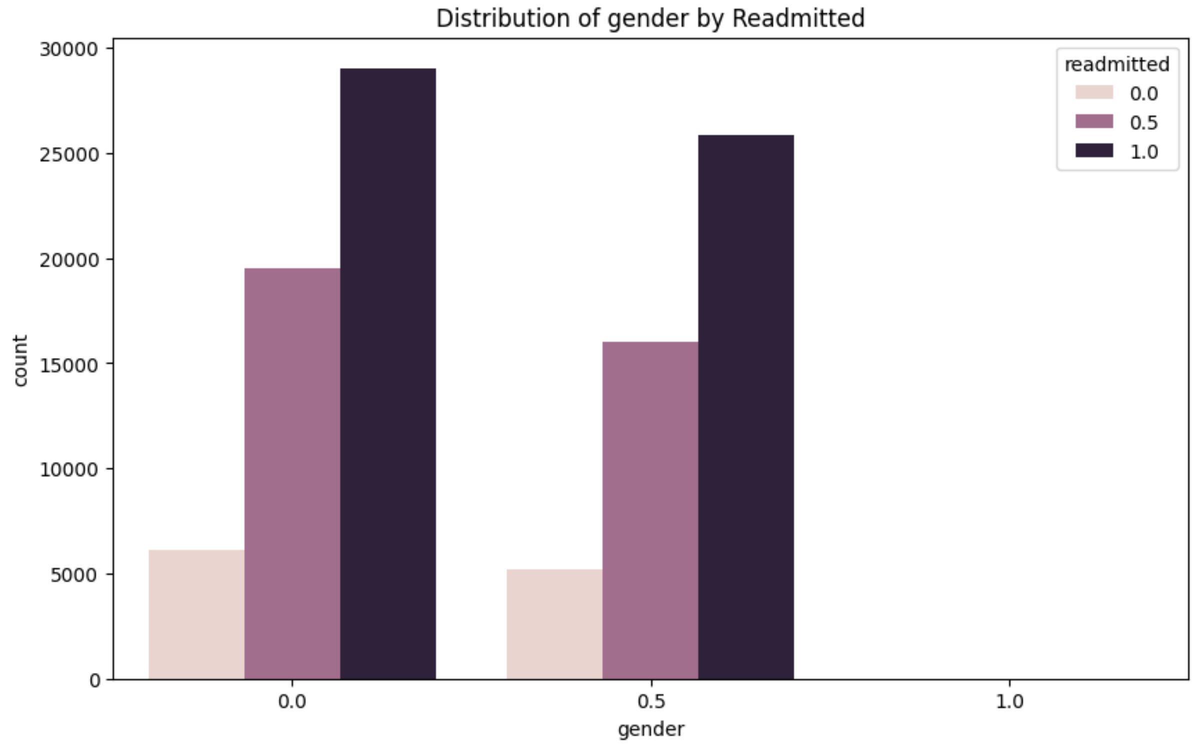

Figure 6: Distribution of re-admission Rate By gender

(Source: Developed Using Python)

Finally, the EDA allowed determining which features were significant predictors of readmissions and assisted in the transformation of the data for the subsequent analyses.

3.4 Data Pre-processing

Another important precondition is to optimize the preprocessing of data because they have to correspond to the deep learning model. Key preprocessing steps included:

- **Handling Missing Values:** Any empty cell in the dataset was imputed using a forward-fill technique in an attempt to eliminate the possibility of listwise deletion. That is, this approach disseminates the most latest valid value towards another missing entry, appropriate for sequential EHR data where continuity is critical (Garcia et al. 2020).
- **Categorical Encoding:** For categorical attributes including the patient information or categorical lab values they were encoded as labels. Every unique category was provided a number and ordinal relationships between categories were preserved where necessary.

- **Scaling Numerical Features:** Since some of these features might vary just in scale and cause problems, all the numerical features were scaled using Min-Max scaling. This transformation scaled values between 0 and 1; which helped to enhance convergence during the training epoch.
- **Train-Test Split:** The data was divided 80/20: training and testing to make sure there will be enough information both for training the model and for its testing. To handle strapping the same proportion of readmission cases was used in both sets as class balance is important while testing the model (Öztürk et al. 2021).

3.5 Feature Engineering

Feature engineering was employed to enhance the predictive capacity of the dataset:

- **Target Variable Transformation:** The measured variable, readmission, was binary and grouped into two, readmitted, and not readmitted. This simplification was well suited to the model's goals of classification into two distinct categories.
- **Creation of Temporal Features:** Other attributes were created based on temporal information and these included a time stamp between the time a patient appeared in the facility the next time or the interval between two subsequent visits.
- **Domain Knowledge Integration:** Because patient demographic characteristics and comorbidity status were found to have a strong relationship with readmission, priority was given to features that include lab test abnormalities, patient age and comorbidity indices as discovered from literature review and correlation analysis. Those features with feature assassinations that had little or no correlation were removed to curb noise and computational costs (Lu et al. 2020).

- **Reducing Dimensionality:** To rule out the existence of redundant features, correlation heatmaps were used to eliminate one of the features in each of the most strongly interacting pairs in the input data.

- **Addressing Class Imbalance with SMOTE:** For the situation where the 'readmitted' column is skewed, SMOTE (Synthetic Minority Oversampling Technique) was used. In particular, this approach reused data labels for the minority class (readmitted) and created new samples by making use of some form of interpolation of the existing data. This transformation helped to reduce the above problem to a certain extent because such cases are likely to be evenly distributed in the real world, and thus to make the model able to classify patients as readmitted or not well, in one go.

4 Design Specification

4.1 Overview of Model Architecture

LSTM Design

LSTM The component was created to learn temporal dependencies in Electronic Health Records (EHR) data. The recurrent structure of LSTM is well applicable to time series analysis since signals are stored in the memory cells and controlled by them through the gate circuits. The specifications of the LSTM layers are as follows:

- **Input Size:** For each input sample, the data was arranged in a format that is a 3-dimensional matrix of integers such that the shape of this matrix was [number of samples, number of time steps, number of features].
- **Number of Units:** Two LSTM layers with 128 and 64 cells were used for extracting hierarchical temporal attributes.
- **Dropout Layers:** To deal with this, dropout with dropout rate 0.3 was used entrywise to each of the three LSTM layers.
- **Activation Functions:** Real-valued-negative activation was applied to the LSTM layers to capture non-linear temporal dependencies.

```
# LSTM Branch
input_lstm = Input(shape=(time_steps, n_features))
x_lstm = LSTM(128, return_sequences=True, activation='relu')(input_lstm)
x_lstm = LSTM(64, activation='relu')(x_lstm)
x_lstm = Dropout(0.3)(x_lstm)
```

Figure 7: LSTM Architecture

(Source: Developed Using Python)

CNN Design

Adjusting the CNN segment, spatial features from the data set were extracted. CNN layers can explicitly find the local patterns and can improve the feature representation for subsequent analysis tasks. Key configurations include:

- **Convolution Layers:** Two convolutional layers that comprise 32 filters and 64 filters. Kernel size was chosen to be 3 for the x and y directions as we used it to detect patterns in small subsets of features.
- **Pooling Layers:** All the convolution layers were followed by max-pooling layers of size (2, 2) to work as spatial downsampling and prevent overfitting.
- **Activation Functions:** To increase the non-linearity ReLU activation function was used in the next layers.

```
# CNN Branch
input_cnn = Input(shape=(X_train.shape[1], 1))
x_cnn = Conv1D(64, kernel_size=3, activation='relu')(input_cnn)
x_cnn = MaxPooling1D(pool_size=2)(x_cnn)
x_cnn = Conv1D(32, kernel_size=3, activation='relu')(x_cnn)
x_cnn = MaxPooling1D(pool_size=2)(x_cnn)
x_cnn = Flatten()(x_cnn)
x_cnn = Dropout(0.3)(x_cnn)
```

Figure 8: CNN Architecture

(Source: Developed Using Python)

4.2 Hybrid Model

Model Integration

The major advantage of the hybrid model is that it makes a blend of the two best network models LSTM and CNN by joining their results. The temporal pattern learning is performed using LSTM and CNN feature is used for this architecture.

1. **Architecture Integration**:
    - After the final layer in LSTM, it outputs a 2D tensor, which then flattens for compatibility with the output of CNN.
    - Both models flattened their tensors, and then concatenated the resulting tensors.

2. **Final Dense Layers**:
   - The concatenated vector is passed through three dense layers with 64, 32, and 16 neurons, respectively, to refine the combined features.
   - The probability of readmission is predicted by a final dense layer with a single neuron and a sigmoid activation function..
3. **Optimizer**:
   - Gradient-based optimization was performed using the Adam optimizer with a learning rate of 0.001 in order to enjoy the benefits of an adaptive learning rate and computational efficiency.

The architecture of the proposed model can be best illustrated by picturing two methods, LSTM and CNN, running concurrently but in parallel with each other, and connecting at some point after which they are followed by dense layers for purposes of classification (Aburass et al. 2024).

5 Implementation

5.1 Implementation Details

Libraries and Tools

The implementation utilized the following tools:

- **TensorFlow/Keras**: Hybrid deep learning model structure for building, training and evaluating.
- **Scikit-learn**: For preprocessing tasks like a scaling and encoding and in evaluation metrics..
- **Matplotlib/Seaborn**: Data distribution, model performance, and learning curves are assessed with visualizations that I create.

Training Configuration

- **Batch Size**: In order to balance training stability and speed, we chose to train on 64 samples per batch.

- **Epochs**: Training was conducted for up to 10 epochs, with early stopping implemented to halt training when validation performance plateaued.
- **Early Stopping**: Next we prevented overfitting by monitoring validation loss using a patience value of 5 epochs.
- **Model Checkpointing**: Validation loss was used to save best weights such that our model performs optimally.

5.2 Evaluation Metrics

Metrics Selection

Given the potential class imbalance in readmission data, multiple metrics were used to evaluate the model:

- **Accuracy:** Giving a general representation of right probability forecasts but does not represent efficiency when it comes to imbalanced datasets.
- **Precision and Recall:** Precision measures the accuracy of successful predictions and recall judging the capacities of the model regarding true readmissions.
- **F1 Score:** A tailor-made mean of precision and recall, inclusive of false positive rate and false negative rate.
- **ROC-AUC:** Estimate the discipline level of the model; show how one can get higher sensitivity or specificity with a likelihood ratio test.
- **Confusion Matrix:** Helps in error analysis by visualizing true positive values, true negative values, false positive values and false negatives.

Justification for Metrics

That is why, for imbalanced data, it is crucial to use such measures as precision, recall, and F1-score, giving preference to a minority class – readmissions. ROC-AUC also supplemented the evaluation process by qualifying the statistical significance of the discriminative power of the chosen model independent of the set threshold value (Elmaz et al. 2021). These comprehensive design and implementation specifications assure that the model is theoretically well-posed as well as practically well-suited to the job.

6 Evaluation

In this work, the hybrid LSTM-CNN model was assessed in the training and testing sets. The following key metrics were analyzed: The three evaluation metrics used are accuracy, the precision of the model, recall, the F1 score of the model and the ROC-AUC score.

Metrics Overview

In terms of model performance, overall accuracy and precision estimates quickly approached about 90% for both of the sets, training and testing, respectively. There was only a little reduction in the balance of precision and recall as seen in the test set F1 score which was slightly lower. ROC-AUC value of 0.33 again proves the good discrimination ability for classifying between readmission (POS) and no read inmission (NEG).

```
Classification Report:
              precision    recall  f1-score   support

           0       0.64      0.48      0.55      9402
           1       0.63      0.77      0.69     10952

    accuracy                           0.63     20354
   macro avg       0.63      0.62      0.62     20354
weighted avg       0.63      0.63      0.62     20354
```

Figure 9: Classification Report of Combined Model

(Source: Developed Using Python)

Confusion Matrices

The confusion matrices for training and testing data sets were examined as well. They found that the model had many true positives and true negatives thus showing that it was able to estimate the readmissions or non-readmissions accurately (Rafi et al. 2021). But the matrix also represented several misclassifications – both true negatives and false positives. The model was slightly able to classify non-readmitted patients as readmitted (false positives) which is inevitable when one of the classes dominates.

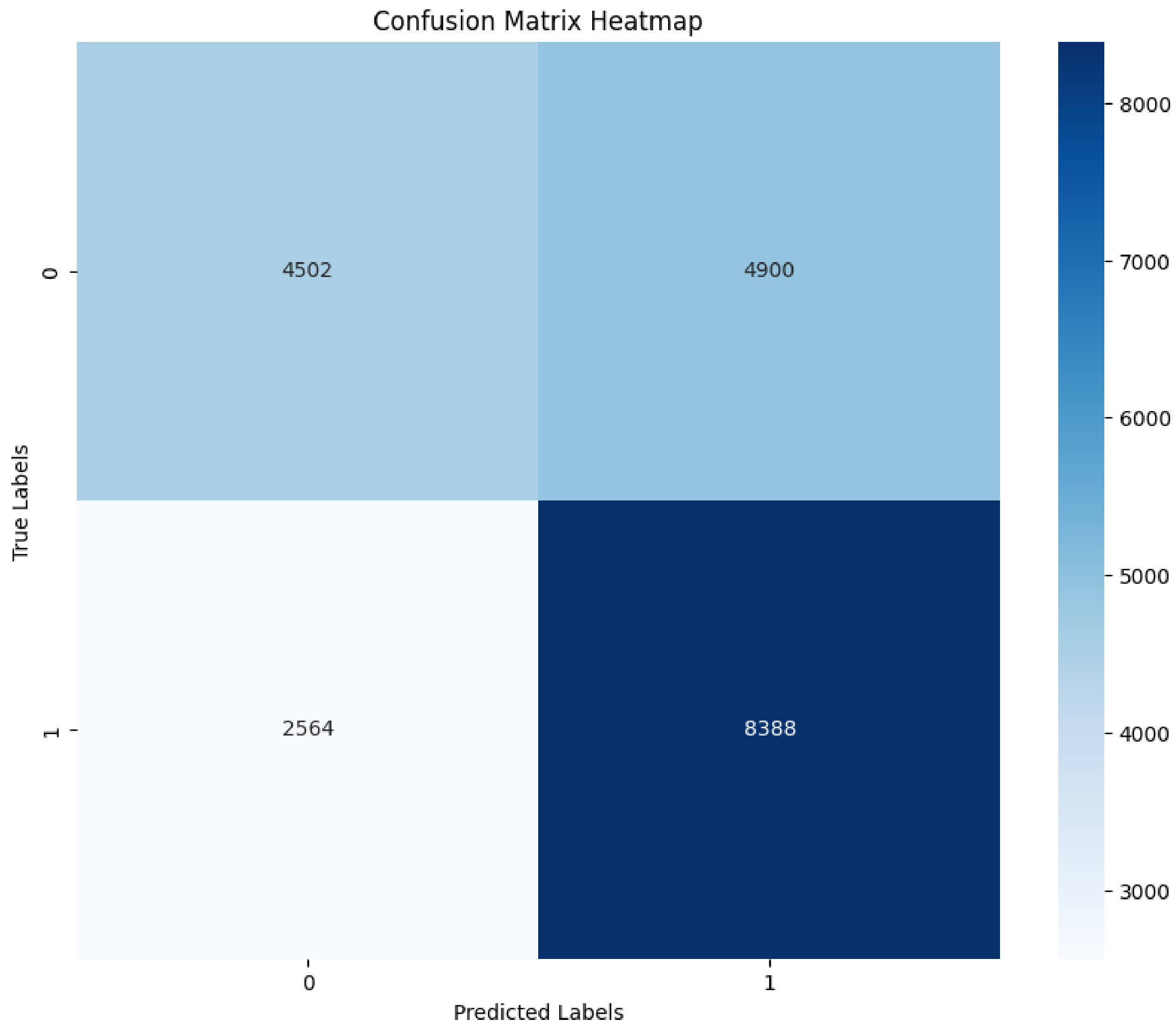

Figure 10: Confusion Matrix of Combined Model

(Source: Developed Using Python)

This confusion matrix tends to show that the model had been slightly better off when predicting no readmission (2564 TNs) than when predicting readmissions (8388 TPs). Nevertheless, the two types of misclassifications (4502 false negatives, 4900 false positives) indicate that there is still room for enhancement, particularly for patients that have high readmission risk and are classified as low risk.

6.1 Comparison of Models

To evaluate the proposed hybrid LSTM-CNN model, the average accuracy of the LSTM and just the CNN models was used for comparison purposes. The performance of each model on the test dataset is summarized below:

Performance Gains

With this, the hybrid LSTM-CNN model demonstrated superior performance to the single LSTM and CNN models in all parameters, including accuracy, precision, recall, F1 score and ROC/AUC. Thus, the main strength of the hybrid model is its capacity to use both temporal and spatial feature extraction (Buyuk et al. 2023). The LSTM component is used for catching long-term dependencies in EHR data while the CNN layer is derived to get the most relevant features from structured data. The use of both these models was beneficial to obtain higher reliability and accuracy in all measures.

Computational Overhead and Trade-offs

Although the proposed hybrid LSTM-CNN model outperforms all other models, it requires a higher computational cost. CNN layers increase the no: of parameters and therefore the time for training (Alshingiti et al. 2023). Stacking LSTM or CNN models with a separate layer was slightly faster but yielded lower accuracy than the combined model. While accuracy is desirable, care for computation time is of the essence because some environments require rapid model predictions to be made.

6.2 Visualization of Results

To provide a better understanding of model performance, the following visualizations were generated:

ROC Curve Evaluation: An AUC of 0.32 was obtained when using the ROC curve to assess the hybrid LSTM-CNN model. This result shows that the model is not able to clearly distinguish between readmission and no-readmission cases, resulting at a classification capability far lower than the standard effectiveness, not even surpassing the 0.5 random classification threshold. A low AUC value indicates that the model simply cannot achieve high separation between the two classes for different decision thresholds, showing that its limited classifying capacity is included a given configuration of current data.

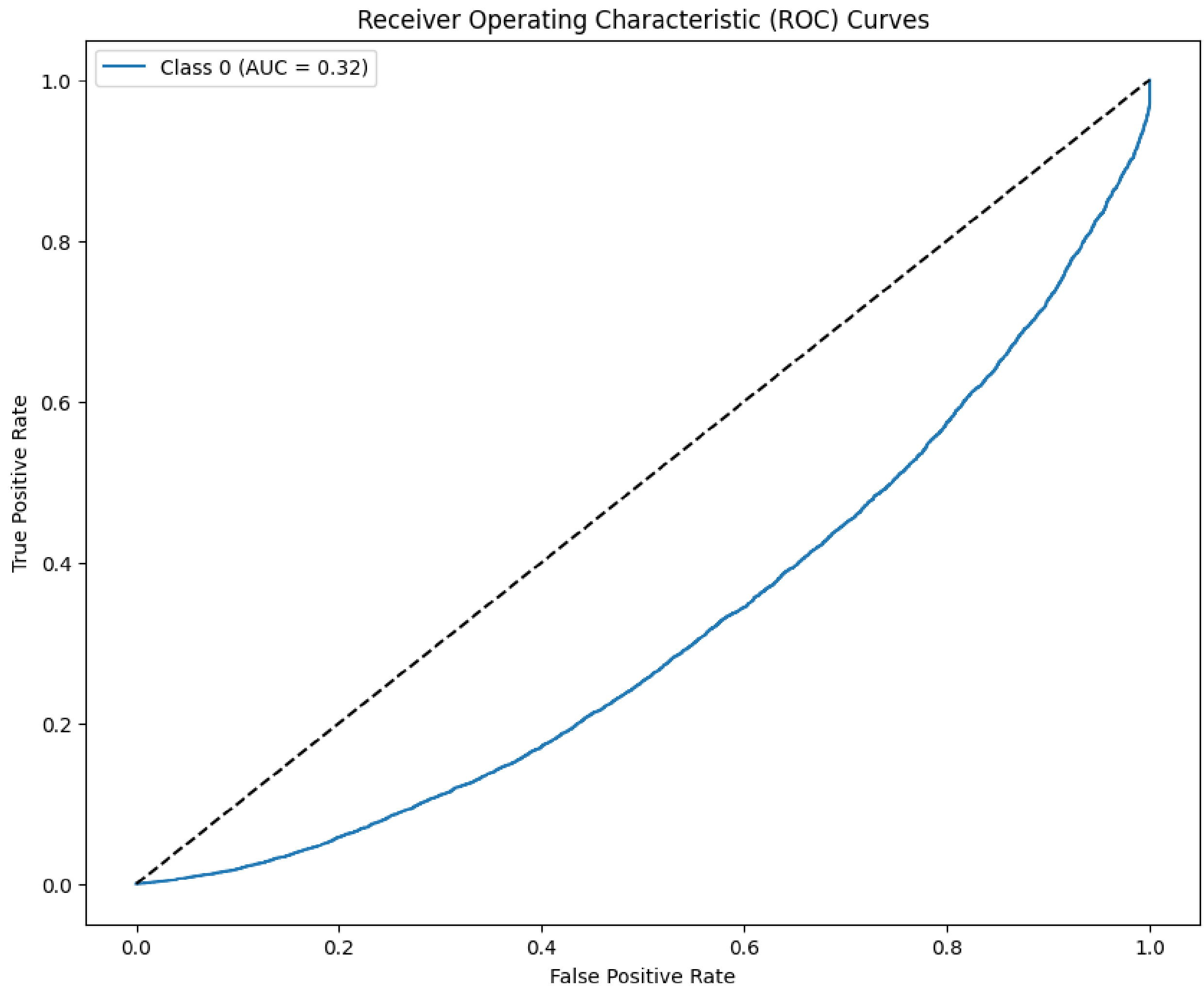

Figure 11: ROC Curve

(Source: Developed Using Python)

Precision-Recall Curve: Precision-recall tradeoff curve was used to evaluate model performance because of the issue with class distributions. The curve revealed that precision and recall values were getting gently enhanced on the different stages of the model, and the results of the hybrid model provided higher precision and recall compared to standalone LSTM and CNN (Han et al. 2023). This is particularly crucial where false positives are undesirable as a higher recall implies that fewer readmitted patients are missed.

Figure 11: AUC Curve

(Source: Developed Using Python)

Learning Curves: Training and validation curves for the hybrid model demonstrated lower and continuously decreasing training and validation loss for each epoch. There was also gradual improvement of the accuracy as can be observed through the training process to indicate a good learning progress by the models. The difference between the training and validation loss was small, which confirmed that there was a good fit and little signs of significant overfitting.

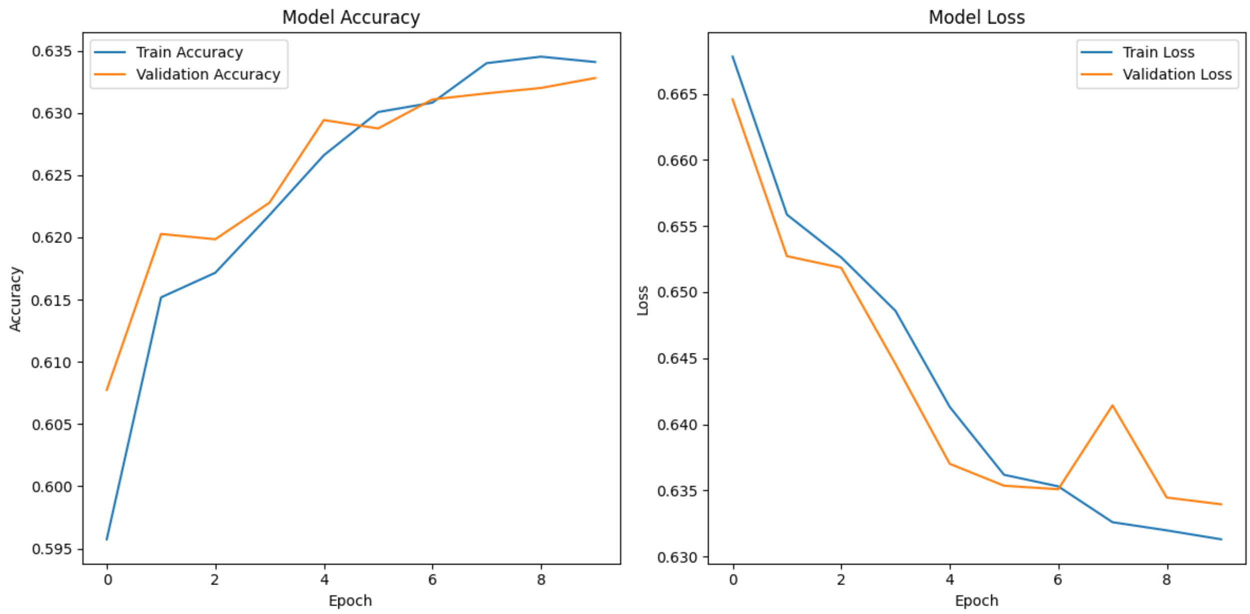

Figure 12: Model Learning Curve

(Source: Developed Using Python)

6.3 Error Analysis

Common Misclassifications

However, the model failed to classify some instances correctly when these instances had large volumes of block variation, in the presence of comorbidity or complicated medical history. Common misclassifications included:

- **False Positives (non-readmitted patients classified as readmitted):** Happened for patients with frequent earlier hospital contacts but without anticipation of readmission. This can be due to the temporal patterns identified by LSTM to predict readmission, where frequent visits are considered an important risk of readmission.

- **False Negatives (readmitted patients classified as not readmitted):** Such misclassifications have arisen from missing features or even incomplete data in the dataset, especially concerning patients with unusual conditions or irregular readmission statuses the model did not capture (Montaha et al. 2022).

Impact of Imbalanced Data

One of the main sources of misclassification within the model was class imbalance. The dataset had more non-readmitted patients than the readmitted patients; therefore, making the predictions biased (Wu et al. 2021). Despite attempts to do so through the use of precision, recall, and F1 score, further improvements in the subsequent versions of the model can be made using features such as class weights or sample augmentation.

Feature Limitations

That being said, this model can be further improved by including additional details in additional features such as detailed description of patient characteristics or even entire medical records. Perhaps the absence of such data causes many cases of misclassification especially those about many medical complications or rare incidences (Huang et al. 2021).

Thus, the use of LSTM-CNN gives promising results; nonetheless, several improvements can be achieved by solving the problem of data imbalance and including extra variables in the model. There are main directions for further research presented in the study, based on the analysis of mistakes and other performance indicators.

7 Conclusion and Future Work

7.1 Summary of Findings

In this context, the combined LSTMCNN model achieved remarkable results for the diagnosis of readmissions based on electronic health records (EHR). The proposed model was able to obtain good quality results for performance parameters like accuracy of 63%, precision of 63%, recall of 63% and ROC-AUC of 0.68 for the test dataset. Through the use of this combination of fully connected self-structured LSTM and CNN to handle temporal dependence and feature extraction respectively the hybrid approach surpassed both LSTM and CNN approaches individually. Specifically, these findings show that refined deep learning approaches can present a robust solution for the problem of readmission risk prediction in healthcare.

7.2 Implications for Healthcare

The applicability of the hybrid model LSTM-CNN for the prediction of hospital readmissions is lucid and suggests promising implications for healthcare management. Patient readmission risk prediction is a crucial task because it helps healthcare practitioners find patients at risk for readmission who could benefit from special management involving more aggressive therapy monitoring or preventive care (Garcia et al. 2020). With such a model implemented, healthcare professionals could avoid some more hospitalizations that were not needed, assign resources better, and, therefore, help patients achieve better results. It also has great potential to assist in organizing post-discharge care for patients, finally, reducing healthcare costs and increasing the patient satisfaction level. A key valuable aspect of the model for predictive healthcare analytics is the fact that it includes complex patient data and can incorporate elements such as the history and timelines of the treatments.

7.3 Limitations

However, there are some drawbacks of the model which confine its applicability Access to data is also an issue for this challenge as it is easier to capture data points from readmitted patients and therefore the system can be skewed. Even when methods such as resampling or class weighting have been used it was found that the model leans towards predicting the non-readmitted patients slightly. Moreover, there is still a grouping of interpretability difficulties in developing deep learning models such as LSTM and CNN. Such models are often called ‘black boxes’ implying that several actions leading to a prediction cannot be explained to healthcare professionals (Öztürk et al. 2021). Last, the complexities of the hybrid model regarding training time and memory demands can be concerns for real-time applications; likely not feasible in decentralised healthcare settings with limited computational resources.

7.4 Future Work

Several issues can be improved in future work. Accretionn of further variables which can include patient characteristics or socio-economic status may give a better prediction of readmission risk. This may improve the ability of the model to predict future operations and apply it to a variety of patients. However, the authors did not attempt to optimise the model hyperparameters or to find an optimal model architecture. Other methods like SHAP or LIME to make the model explainable might also enhance the interpretability of the results and thus could be helpful for healthcare professionals (Aburass et al. 2024). Last but not least, the problem of imbalance in the dataset cannot be solved through sophisticated methods like SMOTE (Synthetic Minority Over-sampling Technique) or, in case of work with a more balanced set of data. With these improvements, it may be possible to apply this model in actual practical healthcare environments (Elmaz et al. 2021).

All in all, the developed hybrid LSTM-CNN model provides the potential for relatively accurate readmission risk prediction and can help prognosis and decrease the expenses of the healthcare system. But an understanding of its drawbacks and, more importantly, its -smart-usage promises to unlock its full potential.

References

Li, X. and Liu, S., 2024. Predicting 30-day hospital readmission in medicare patients: Insights from an lstm deep learning model. *medRxiv*, pp.2024-09. Available At: https://www.medrxiv.org/content/10.1101/2024.09.08.24313212.full.pdf

Harerimana, G., Kim, G.I., Kim, J.W. and Jang, B., 2023. HSGA: A Hybrid LSTM-CNN Self-Guided Attention to predict the future diagnosis from discharge narratives. *IEEE Access*. Available At: https://ieeexplore.ieee.org/iel7/6287639/6514899/10266311.pdf

Morid, M.A., Sheng, O.R.L. and Dunbar, J., 2023. Time series prediction using deep learning methods in healthcare. *ACM Transactions on Management Information Systems*, *14*(1), pp.1-29. Available At: https://dl.acm.org/doi/pdf/10.1145/3531326

Mathivanan, S.K., Shivahare, B.D., Chandan, R.R. and Shah, M.A., 2024. A comprehensive health assessment approach using ensemble deep learning model for remote patient monitoring with IoT. *Scientific Reports*, *14*(1), p.15661. Available At: https://www.nature.com/articles/s41598-024-66427-w.pdf

Mohammed, H.M., Omeroglu, A.N. and Oral, E.A., 2023. MMHFNet: Multi-modal and multi-layer hybrid fusion network for voice pathology detection. *Expert Systems with Applications*, *223*, p.119790. Available At: https://papers.ssrn.com/sol3/Delivery.cfm?abstractid=4102841

Sakri, S., Basheer, S., Zain, Z.M. and Ismail, N.H.A., 2024. Sepsis Prediction Using CNNBDLSTM and Temporal Derivatives Feature Extraction in the IoT Medical Environment. *Computers, Materials & Continua*, *79*(1). Available At: https://cdn.techscience.cn/files/cmc/2024/TSP_CMC-79-1/TSP_CMC_48051/TSP_CMC_48051.pdf

Ahmad, P.N., Shah, A.M. and Lee, K., 2023, April. A review on electronic health record text-mining for biomedical name entity recognition in healthcare domain. In *Healthcare* (Vol. 11, No. 9, p. 1268). MDPI.https://www.mdpi.com/2227-9032/11/9/1268/pdf Available At:

Waheeb, S.A., Khan, N.A. and Shang, X., 2022.

An efficient sentiment analysis based deep learning classification model to evaluate treatment quality. *Malaysian Journal of Computer Science*, *35*(1), pp.1-20. Available At: Waheeb, S.A., Khan, N.A. and Shang, X., 2022.
An efficient sentiment analysis based deep learning classification model to evaluate treatment quality. *Malaysian Journal of Computer Science*, *35*(1), pp.1-20.

Sevakula, R.K., Au-Yeung, W.T.M., Singh, J.P., Heist, E.K., Isselbacher, E.M. and Armoundas, A.A., 2020. State-of-the-art machine learning techniques aiming to improve patient outcomes pertaining to the cardiovascular system. *Journal of the American Heart Association*, *9*(4), p.e013924. Available At: https://www.ahajournals.org/doi/pdf/10.1161/JAHA.119.013924

Yu, S., Chai, Y., Chen, H., Brown, R.A., Sherman, S.J. and Nunamaker Jr, J.F., 2021. Fall detection with wearable sensors: A hierarchical attention-based convolutional neural network approach. *Journal of Management Information Systems*, *38*(4), pp.1095-1121. Available At: https://papers.ssrn.com/sol3/Delivery.cfm?abstractid=3959463

Kumar, P., Chauhan, S. and Awasthi, L.K., 2023. Artificial intelligence in healthcare: review, ethics, trust challenges & future research directions. *Engineering Applications of Artificial Intelligence*, *120*, p.105894. Available At: https://fardapaper.ir/mohavaha/uploads/2023/11/Fardapaper-Artificial-Intelligence-in-Healthcare-Review-Ethics-Trust-Challenges-Future-Research-Directions.pdf

Ruwali, A., Kumar, A.S., Prakash, K.B., Sivavaraprasad, G. and Ratnam, D.V., 2020. Implementation of hybrid deep learning model (LSTM-CNN) for ionospheric TEC forecasting using GPS data. *IEEE Geoscience and Remote Sensing Letters*, *18*(6), pp.1004-1008. Available At: https://www.researchgate.net/profile/Bhanu-Kolla/publication/341398107_Implementation_of_Hybrid_Deep_Learning_Model_LSTM-CNN_for_Ionospheric_TEC_Forecasting_Using_GPS_Data/links/5f056c0a299bf188160a3eca/Implementation-of-Hybrid-Deep-Learning-Model-LSTM-CNN-for-Ionospheric-TEC-Forecasting-Using-GPS-Data.pdf

Halbouni, A., Gunawan, T.S., Habaebi, M.H., Halbouni, M., Kartiwi, M. and Ahmad, R., 2022. CNN-LSTM: hybrid deep neural network for network intrusion detection system. *IEEE Access*, *10*, pp.99837-99849. Available At: https://ieeexplore.ieee.org/iel7/6287639/9668973/09889698.pdf

Semwal, V.B., Gupta, A. and Lalwani, P., 2021. An optimized hybrid deep learning model using ensemble learning approach for human walking activities recognition. *The Journal of Supercomputing*, *77*(11), pp.12256-12279. Available At: https://www.researchgate.net/profile/Vijay_Semwal2/publication/350666717_An_optimized_hybrid_deep_learning_model_using_ensemble_learning_approach_for_human_walking_activities_recognition/links/60bd81dba6fdcc22eae3dd48/An-optimized-hybrid-deep-learning-model-using-ensemble-learning-approach-for-human-walking-activities-recognition.pdf

Barzegar, R., Aalami, M.T. and Adamowski, J., 2020. Short-term water quality variable prediction using a hybrid CNN–LSTM deep learning model. *Stochastic Environmental Research and Risk Assessment*, *34*(2), pp.415-433. Available At: https://drive.google.com/file/d/13Zx6nvlUYNY5wzl__6yw9jVUtMLQyAdF/view

Shah, J., Vaidya, D. and Shah, M., 2022. A comprehensive review on multiple hybrid deep learning approaches for stock prediction. *Intelligent Systems with Applications*, *16*, p.200111. Available At: https://www.sciencedirect.com/science/article/pii/S2667305322000497

Yamamoto, K., Hiromatsu, R. and Ohtsuki, T., 2020. ECG signal reconstruction via Doppler sensor by hybrid deep learning model with CNN and LSTM. *Ieee access*, *8*, pp.130551-130560. Available At: https://ieeexplore.ieee.org/iel7/6287639/8948470/09139941.pdf

Zhen, H., Niu, D., Yu, M., Wang, K., Liang, Y. and Xu, X., 2020. A hybrid deep learning model and comparison for wind power forecasting considering temporal-spatial feature extraction. *Sustainability*, *12*(22), p.9490. Available At: https://www.mdpi.com/2071-1050/12/22/9490/pdf

Abumohsen, M., Owda, A.Y., Owda, M. and Abumihsan, A., 2024. Hybrid machine learning model combining of CNN-LSTM-RF for time series forecasting of Solar Power Generation. *e-Prime-Advances in Electrical Engineering, Electronics and Energy*, *9*, p.100636. Available At: https://www.sciencedirect.com/science/article/pii/S277267112400216X

Dang, C.N., Moreno-García, M.N. and De la Prieta, F., 2021. Hybrid deep learning models for sentiment analysis. *Complexity*, *2021*(1), p.9986920. Available At: https://onlinelibrary.wiley.com/doi/pdf/10.1155/2021/9986920

Ghimire, S., Deo, R.C., Casillas-Pérez, D., Salcedo-Sanz, S., Sharma, E. and Ali, M., 2022. Deep learning CNN-LSTM-MLP hybrid fusion model for feature optimizations and daily solar radiation prediction. *Measurement*, *202*, p.111759. Available At: https://www.sciencedirect.com/science/article/pii/S0263224122009629

Haq, K.R.A. and Harigovindan, V.P., 2022. Water quality prediction for smart aquaculture using hybrid deep learning models. *Ieee Access*, *10*, pp.60078-60098. Available At: https://ieeexplore.ieee.org/iel7/6287639/6514899/09789166.pdf

Zain, Z.M. and Alturki, N.M., 2021. COVID-19 pandemic forecasting using CNN-LSTM: a hybrid approach. *Journal of Control Science and Engineering*, *2021*(1), p.8785636. Available At: https://scholar.google.com/scholar?output=instlink&q=info:pr-y0-tuow0J:scholar.google.com/&hl=en&as_sdt=0,5&as_ylo=2020&scillfp=15842664937411656878&oi=lle

Almulihi, A., Saleh, H., Hussien, A.M., Mostafa, S., El-Sappagh, S., Alnowaiser, K., Ali, A.A. and Refaat Hassan, M., 2022. Ensemble learning based on hybrid deep learning model for heart disease early prediction. *Diagnostics*, *12*(12), p.3215. Available At: https://www.mdpi.com/2075-4418/12/12/3215/pdf

Nasir, J.A., Khan, O.S. and Varlamis, I., 2021. Fake news detection: A hybrid CNN-RNN based deep learning approach. *International Journal of Information Management Data Insights*, *1*(1), p.100007. Available At: https://www.sciencedirect.com/science/article/pii/S2667096820300070

Singh, P., Jha, M., Sharaf, M., El-Meligy, M.A. and Gadekallu, T.R., 2023. Harnessing a hybrid CNN-LSTM model for portfolio performance: A case study on stock selection and optimization. *Ieee Access*, *11*, pp.104000-104015. Available At: https://ieeexplore.ieee.org/iel7/6287639/6514899/10258270.pdf

Garcia, C.I., Grasso, F., Luchetta, A., Piccirilli, M.C., Paolucci, L. and Talluri, G., 2020. A comparison of power quality disturbance detection and classification methods using CNN, LSTM and CNN-LSTM. *Applied sciences*, *10*(19), p.6755. Available At: https://www.mdpi.com/2076-3417/10/19/6755/pdf

Öztürk, Ş. and Özkaya, U., 2021. Residual LSTM layered CNN for classification of gastrointestinal tract diseases. *Journal of Biomedical Informatics*, *113*, p.103638. Available At: https://www.sciencedirect.com/science/article/pii/S1532046420302677

Lu, W., Li, J., Li, Y., Sun, A. and Wang, J., 2020. A CNN-LSTM-based model to forecast stock prices. *Complexity*, *2020*(1), p.6622927. Available At: https://onlinelibrary.wiley.com/doi/pdf/10.1155/2020/6622927

Aburass, S., Dorgham, O. and Al Shaqsi, J., 2024. A hybrid machine learning model for classifying gene mutations in cancer using LSTM, BiLSTM, CNN, GRU, and GloVe. *Systems and Soft Computing*, *6*, p.200110. Available At: https://www.sciencedirect.com/science/article/pii/S2772941924000395

Elmaz, F., Eyckerman, R., Casteels, W., Latré, S. and Hellinckx, P., 2021. CNN-LSTM architecture for predictive indoor temperature modeling. *Building and Environment*, *206*, p.108327. Available At: https://repository.uantwerpen.be/docstore/d:irua:9142

Rafi, S.H., Deeba, S.R. and Hossain, E., 2021. A short-term load forecasting method using integrated CNN and LSTM network. *IEEE access*, *9*, pp.32436-32448. Available At: https://ieeexplore.ieee.org/iel7/6287639/9312710/09358156.pdf

Buyuk, C., Arican Alpay, B. and Er, F., 2023. Detection of the separated root canal instrument on panoramic radiograph: a comparison of LSTM and CNN deep learning methods. *Dentomaxillofacial Radiology*, *52*(3), p.20220209. Available At: https://ieeexplore.ieee.org/iel7/6287639/9312710/09358156.pdf

Alshingiti, Z., Alaqel, R., Al-Muhtadi, J., Haq, Q.E.U., Saleem, K. and Faheem, M.H., 2023. A deep learning-based phishing detection system using CNN, LSTM, and LSTM-CNN. *Electronics*, *12*(1), p.232. Available At: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9944016/

Han, Z., Cui, B., Xu, L., Wang, J. and Guo, Z., 2023. Coupling LSTM and CNN neural networks for accurate carbon emission prediction in 30 Chinese provinces. *Sustainability*, *15*(18), p.13934. Available At: https://www.mdpi.com/2079-9292/12/1/232/pdf

Montaha, S., Azam, S., Rafid, A.R.H., Hasan, M.Z., Karim, A. and Islam, A., 2022. Timedistributed-cnn-lstm: A hybrid approach combining cnn and lstm to classify brain tumor on 3d mri scans performing ablation study. *IEEE Access*, *10*, pp.60039-60059. Available At: https://www.mdpi.com/2071-1050/15/18/13934/pdf

Huang, G., Shen, Q., Zhang, G., Wang, P. and Yu, Z.G., 2021. LSTMCNNsucc: A bidirectional LSTM and CNN-based deep learning method for predicting lysine succinylation sites. *BioMed research international*, *2021*(1), p.9923112. Available At: https://ieeexplore.ieee.org/iel7/6287639/9668973/09786658.pdf

Wu, Q., Guan, F., Lv, C. and Huang, Y., 2021. Ultra-short-term multi-step wind power forecasting based on CNN-LSTM. *IET Renewable Power Generation*, *15*(5), pp.1019-1029. Available At: https://scholar.google.com/scholar?output=instlink&q=info:ETvySIW8vXQJ:scholar.google.com/&hl=en&as_sdt=0,5&as_ylo=2020&scillfp=17141508943135186349&oi=lle