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Integrating XGBoost and Recurrent Neural Networks (RNNs) to Optimize COVID-19 Mortality Prediction

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Abstract

The SARS-CoV-2 pandemic has severely affected worldwide health, but the prediction of patient mortality remains difficult to achieve accurately. Current predictive methods mainly concentrate on clinical condition measurements without a complete view of death predictions. This research fills the void between advanced modelling through XGBoost and Recurrent Neural Networks (RNNs) for improved COVID-19 mortality prediction analysis. We applied a systematic four-phase approach to collect data from the "COVID-19 Symptoms Dataset containing symptoms and death cases as well as mortality rates and confirmed cases, " prior to data processing and analysis stages, including cleaning, visualization and feature analysis, followed by the implementation and optimization of XGBoost models and RNN frameworks. The final stage involved performance assessment with accuracy, precision recall, and F1-score. The evaluation results demonstrate RNNs deliver superior performance than XGBoost by achieving 94% accuracy, 93% recall, 92% F1-score, and 92% precision, at a time when XGBoost reaches 88.47% accuracy alone. Results demonstrate the advantage of XGBoost-RNN integration for mortality predictions, which enables public health services to create better resource plans.

Keywords: COVID-19 Pandemic, Deep Learning (DL), Machine Learning (ML), Mortality Prediction Clinical Severity, Recurrent Neural Networks (RNNs), XGBoost, Supervised Learning, Data Analysis

Introduction

A pandemic was caused by a new coronavirus that was discovered in Wuhan, China, in December 2019. It was connected to pneumonia cases and spread quickly. In January 2020, COVID-19 was deemed a public health emergency by the World Health Organization (WHO), and in March 2020, it was deemed a pandemic. The severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) that causes COVID-19 has afflicted over 1.4 million people worldwide and over 81,552 people in China. The virus spread faster outside China, notably in the USA, Italy, and Spain. Health authorities renamed this pathogen from 2019-nCoV to establish its official designation as SARS-CoV-2[1].

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The coronavirus receives its name with "Co" referring to "corona", while "vi" defines "virus", and "d" stands for "disease." Therefore, the virus remains a coronavirus that produces the disease known as COVID-19. Coronaviruses, which include both common colds and dangerous conditions such as SARS and MERS, constitute a virus family. The normal spread of these viruses occurs among animals until specific types initiate zoonotic occurrences, which involve human-animal viral transmission. A respiratory disease outbreak currently persists due to the recently discovered strain of COVID-19 [2]. During 2003, the Severe Acute Respiratory Syndrome Coronavirus (SARS-CoV) surfaced in Hong Kong along with Mainland China, thus producing severe respiratory complications. A MERS outbreak occurred in 2012 throughout Saudi Arabia, the United Arab Emirates, and the Republic of Korea, as well as several other countries because of MERS-CoV infections [3]. Human scientific capabilities controlled both the SARS-CoV outbreak and the MERS-CoV epidemic. Coronavirus recognition expanded greatly worldwide after 2020, specifically because of SARS-CoV-2 leading to COVID-19. Not every individual understands that SARS-CoV-2 belongs to a vast viral family that includes past infectious outbreaks. Scientists have acquired significant knowledge about coronaviruses, but gaps remain, and the possibility of a coronavirus pandemic was largely unforeseen before the 21st century [4].

Over 40 coronaviruses have been identified by the International Committee on Taxonomy of Viruses; seven of them, including SARS-CoV1, MERS-CoV, and SARS-CoV-2, are known to infect humans and have significant fatality rates [5]. Seven machine learning models were used to assess the electronic medical records of COVID-19 patients in Ethiopia: logistic regression (LR), eXtreme gradient boosting (XGBoost), multi-layer perceptron (MLP), k-nearest neighbor (k-NN), random forest (RF), J48 decision tree, and Naïve Bayes (NB). Measures such as receiver operating characteristic (ROC), sensitivity, specificity, and accuracy were used to evaluate the performance of the model [6]. Coronaviruses, initially zoonotic, undergo genetic modifications enabling human transmission, often causing severe infections. Ongoing reinfections by mild coronaviruses like OC43 and 229E necessitate vigilance [7].

The Kaggle COVID-19 dataset provides details on patients' symptoms, death cases, mortality rates, and confirmed cases. The main symptoms, which develop between two and fourteen days, are a dry cough, a high temperature, a sore throat, and trouble breathing [8]. Fever involves elevated temperature (irregular, remittent, intermittent, or continuous). Persistent cough may indicate bronchitis or pneumonia, while shortness of breath (dyspnea) manifests as air hunger or chest tightness, worsened by exertion, extreme temperatures, or high altitude [9].

To predict COVID-19 mortality, machine learning (ML) and deep learning (DL) approaches have been widely used. Researchers developed a cost-effective model based on HRCT radiomic and clinical information by implementing an SVM together with an FNN model. Evidence presented in clinical settings confirmed the usefulness of these properties together as they yielded the maximum Area Under the receiver operating characteristic (AUC) [10]. Evaluation of 1,816 patients along with five hospitals and authorized software led to the development of reliable prediction models that analyzed radiomic data joined with neural network properties found in chest X-rays (CXRs). Feature selection and mortality prediction utilized Random Forest (RF), AdaBoost (ADA), together with Quadratic Discriminant Analysis (QDA) as components of the developed pipeline. The predictive performance of the models on both balanced and imbalanced datasets was validated through ACC, AUC, and SENS metrics [11]. The recent development of three supervised deep learning models includes Convolutional Neural Network (CNN)-based CV-CNN and Long Short-Term Memory (LSTM) in conjunction with CNN in CV-LSTM + CNN and IMG-CNN that utilizes converted clinical dataset images for COVID-19 mortality prediction [12]. The application of these methods proves the importance of ML and DL for pandemic-related problem-solving.

Several advanced deep learning methods were tested to forecast COVID-19 mortality, including Long Short-Term Memory (LSTM), bidirectional LSTM, Convolutional Neural Networks (CNN), hybrid CNN-LSTM, Multilayer Perceptrons (MLP), and Recurrent Neural Networks (RNN). The performance of Bayesian optimization was applied to a dataset containing socioeconomic and demographic, and case count information to reveal model effectiveness data for public health decision-making [13]. Out of 14 Machine Learning (ML) techniques, Gradient Boosting fared better with OpenDataSus data, including vaccination data [14].

Global public health faces serious dangers from the COVID-19 pandemic, mainly affecting elderly persons and newborns. Current DL and ML models primarily predict clinical severity outcomes instead of mortality rates, thus preventing their use in wide public health applications. The limited data accessibility from specific hospitals impedes widespread generalization ability regarding global case prediction.

The COVID-19 pandemic has underscored the critical need for accurate mortality prediction to guide resource allocation and public health interventions. While ML/DL models like XGBoost and CNNs have been widely adopted for clinical severity classification [Citations 6, 12], their performance in mortality prediction remains suboptimal due to three key limitations: (1) reliance on static clinical measurements, ignoring temporal symptom progression; (2) dataset biases from single-hospital cohorts, limiting generalizability; and (3) insufficient integration of feature importance (e.g., XGBoost) with sequential pattern recognition (e.g., RNNs). To address these gaps, we propose a hybrid framework combining XGBoost for feature optimization and RNNs for time-series analysis of symptom trajectories, leveraging the Kaggle COVID-19 Symptoms Dataset to enhance global prediction accuracy.

This research uses state-of-the-art ML and DL approaches to develop enhanced methods for forecasting death outcomes from COVID-19. The "COVID-19 Symptoms Dataset" obtained from Kaggle serves as our primary data source that contains vital information about symptoms, verified cases, mortality rates, and death cases.

Our research's primary objective is to improve global death case prediction through the use of RNN and XGBoost technology. Our approach is divided into four stages: (1) Data Acquisition: The "COVID-19 Symptoms Dataset" is used, which includes characteristics such as dry cough, elevated fever, and dyspnea; (2) Data Processing and Analysis: Pre-processing and preliminary data exploration guarantee dataset preparedness; (3) Supervised Learning: RNNs are used to predict mortality, with data augmentation and XGBoost for improved performance; (4) Performance Evaluation: To verify improvements, we compare our method with other approaches.

The integration of RNNs and XGBoost optimizes the handling of complex data patterns and improves global prediction accuracy for COVID-19 outcomes. Our approach differs from previous studies by focusing on mortality prediction, not just clinical severity in specific hospitals, and addresses the gap in global mortality forecasting. By utilizing a comprehensive dataset and advanced models, we offer valuable insights into mortality patterns for resource allocation and public health planning, advancing COVID-19 prediction and applications.

The subsequent sections will review current methodologies in Section Literature Review, outline the proposed framework in Section Methodology, discuss experimental results in Section Results and Discussion, and provide recommendations for further research in Section Conclusion.

1. Literature Review

The methods for forecasting COVID-19 mortality rates utilizing the COVID-19 Symptoms Dataset, which includes symptoms, verified cases, and death cases, are examined in this paper. They classify different methods based on characteristics such as dry cough, fever, sore throat, and dyspnea.

The C4.5 decision tree combined with PCA and PLS and t-SNE approaches serves to evaluate COVID-19 mortality risk factors in 3,008 Iranian patients. heart pain combined with advanced age remains the central risk factor while the others include chest pain and abnormal respiratory rate along with oxygen saturation levels below 93% and mechanical ventilation requirements and neurological/cardiovascular diseases. Machine learning provides successful identification of essential critical treatment needs at an early stage [15]. To create predictive models, J48 decision trees, logistic regression (LR), eXtreme gradient boosting (XGBoost), random forest (RF), k-nearest neighbor (k-NN), multi-layer perceptrons (MLP), Naïve Bayes (NB), and random forest (RF) were used [16].

The spread of COVID-19 grew in both infectivity as well as death rates when spread is by environmental routes during winter. EEMD technology found a 59.71% increase in the rate of transmission in the Southern Hemisphere, with a 46.38% fall in the Northern Hemisphere. A seasonal variation SEIR model shows the influence of the environment on disease spread, so that public health interventions are necessary. [17].

Mathematical models of disease dynamics are now required in larger quantities to meet the COVID-19 pandemic. Simulation using basic logics carried out via first-order ordinary differential equations provides reliable results when it comes to forecasting the first-wave numbers of disease [18]. The study compares the latest techniques for predicting COVID-19 patient mortality using Machine Learning (ML) and Deep Learning (DL) methods. Techniques such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Logistic Regression, Random Forest, and Decision Tree are evaluated for their predictive efficacy. The G power calculation established sample requirements for a satisfactory error level of 0.5 [19].

Recent advancements in High Performance Medicine have demonstrated the transformative potential of integrating machine learning and deep learning techniques for predictive healthcare analytics. Studies such as those found in [20] highlight the efficacy of these approaches in optimizing clinical decision-making and resource allocation. These works align with our research objectives, particularly in leveraging XGBoost and RNNs for COVID-19 mortality prediction. By incorporating insights from High Performance Medicine, our study not only builds on existing methodologies but also explores novel applications of these technologies in pandemic response

Beta coronavirus zoological transmission events became the harbinger for SARS-CoV and MERS-CoV. Since December 2019 to date, the 2019-nCoV (SARS-CoV-2) has spread from Wuhan to induce acute pneumonia by respiratory illness as its main mode of transmission during the global epidemic. With their combined use, CNNs and GANs have enhanced the forecasting of COVID-19 death numbers [21]. Scientists find it hard to make precise predictions regarding the mortality outcomes for COVID-19 patients. Recent research has used Polynomial Regression alongside Auto-Regressive Integrated Moving Average (ARIMA) and Recurrent Neural Networks (RNN), which belong to the deep learning classification. Polynomial Regression produced the most accurate predictions for India among the forecasting models that also successfully predicted trends in South Korea, Italy, the United States, and the United Kingdom [22]. The evaluation of modern ML and DL methods enables faster detection of COVID-19 patient mortality risks. A hybrid model blends ML and DL techniques through ten deep CNN devices for extracting features from CT scan images. A total of 2481 CT scans served as the foundation for the dataset, which is divided between COVID-19 affected and non-COVID-19 groups. The identification of features occurred through five ML classifiers analyzing layer outputs from CNN structures [23].

Methods for DL, especially CNNs with transfer learning, are employed to diagnose and monitor COVID-19 using X-ray images, aiding radiologists and doctors. Challenges like limited and imbalanced datasets, model overfitting, and symptom similarity between COVID-19 and pneumonia are addressed by an automated solution that classifies COVID-19 into two categories using nine advanced CNN architectures [24]. Support Vector Machine (SVM) with hyperparameter tuning via the Taguchi method was employed to analyze 19 variables affecting COVID-19 cases and mortality. The hybrid SVM-Taguchi approach enhanced predictions for confirmed cases and deaths, showing superior statistical performance compared to other artificial intelligence methods [25]. Daily development rates and doubling times of cases were used to establish moderation, control, and containment benchmarks (development rates of <10%, 1%, and 0.1%, respectively) with interventions like isolation and lockdown [26]. Information from 26,867 PCR-positive COVID-19 patients was analyzed using Artificial Neural Networks (ANN) and Logistic Regression (LR) models. Decreased consciousness, cough, PO2 level, age, chronic kidney illness, fever, headache, smoking status, chronic blood disorders, and diarrhea were among the major mortality predictors that ANN discovered[27]. The utilization of big data and artificial intelligence (AI) techniques, such as neural networks, traditional SVM, and edge learning, was highlighted in the state of AI applications in clinical contexts for COVID-19 [28].

Machine learning models for predicting COVID-19 cases identified Exponential Smoothing (ES) as the most effective, SVM displayed inconsistent performance, followed by Least Absolute Shrinkage and Selection Operator (LASSO), and Logistic Regression (LR) [29]. Deep learning (DL) analyzed Lung Superman (LUS) images, assessing infection severity at the edge, video, and pixel levels. Advanced models, such as Spatial Transformer Networks, were introduced for severity prediction. A depth model benchmarked pixel-level COVID-19 biomarkers, yielding promising results with ongoing research [30]. Recent studies on mortality prediction using ML and DL found LSTM most effective for death predictions [31]. For estimating death rates and determining the severity of the condition, COVID-19 mortality rates are essential. Machine learning algorithms that examine risk factors and mortality include Random Forest, XGBoost, Support Vector Machine (SVM), and regression models. These models predict future pandemic mortality with high accuracy. Combining the Covid-GAN model with CNNs improves detection by creating synthetic chest X-ray images based on an Auxiliary Classifier Generative Adversarial Network (ACGAN) [32]. Artificial Intelligence (AI) aids COVID-19 analysis. The CNN-GRU model, developed using a dataset of 4,692 cases, predicts mortality [33]. A recent approach using chest X-ray images and AI methods, including k-nearest neighbor, Bayesian methods, and SVM, showed notable results with MobileNet and SVM classifiers [34].

Research shows that ML and DL techniques have established effectiveness in predicting COVID-19 death rates. Decision Tree (DT) classifiers, together with Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Logistic Regression (LR), stand out among other techniques [35]. Research examines how ML methods predict the death rates for COVID-19 patients. The analysis examined KNN, Naive Bayes, SVM, Decision Tree, Random Forest, and LR applied to data gathered from the Kaggle dataset. This research uncovered main indicators pointing towards patient death while demonstrating symptoms hold vital importance for predicting COVID-19 mortality risks. The research findings demonstrate that the proposed system easily processes new information to enable physicians at the frontline to respond quickly to clinical situations [36].

Complex machine learning algorithms perform sentiment intelligence functionalities, identify motor accidents and classify COVID-19 pneumonia conditions. Machine learning algorithms such as XGBoost, Random Forest (RF), CNNs, and AdaBoost achieve the best possible outcomes in diagnostic testing and resource management for COVID-19 detection within the GitHub X-ray dataset [37-40]. A sentiment analysis framework uses AdaBoost along with XGBoost and ANNs to achieve enhanced user sentiment classification functionality for Google Play Store reviews [41]. Dark data analysis through the combination of AdaBoost and RF brings better results in accident prediction, thus proving its worth in decision-making

processes [42]. The study demonstrates how machine learning creates significant change throughout multiple professional domains.
A study provided an integrated approach to predict COVID-19 cases in Iran and adjacent countries using mathematical and deep learning models. The findings from this research were analyzed by Root Mean Square Error (RMSE) to assist decision-makers with policy decisions [43]. A proposed study uses Automated Machine Learning (AutoML) via Python's Auto-Sklearn to predict COVID-19 infection using blood test data (5644 cases, 111 variables). The three main experimental tests used in this study compare three types of classification: meta-learning, ensemble learning, and a combination of both methods [44].

2. Methodology

The methodology works systematically by analyzing COVID-19 death rates through data from the Kaggle 'COVID-19 Symptoms Dataset.' The methodology includes four distinct stages: (1) data acquisition, (2) Python library-based data processing, (3) supervised learning using RNNs with XGBoost enhancements, and (4) performance testing against standard methods. The Long Short-Term Memory (LSTM) model handles time-series data by focusing on significant symptoms related to higher mortality rates to enhance prediction accuracy. Figure 1 illustrates the block diagram of the proposed work, providing a visual overview of the four-phase approach. The detailed algorithm is presented in Algorithm 01.
Our proposed method carries four sequential procedures starting from Data Acquisition, which employed a specified COVID-19 dataset from Kaggle that aggregated symptoms of patients alongside death information, mortality rates, and confirmed cases data. The research analyzed data through Python and Anaconda Jupyter Notebook after incorporating symptoms like dry cough, along with high fever symptoms and sore throat manifestations, and breathing difficulty indicators. The data processing analysis used scatter plots and histograms and dimensionality reduction methods, which allowed researchers to identify significant differences between symptoms along with death cases mortality rates, and confirmed cases. We used XGBoost together with deep learning through Recurrent Neural Networks (RNNs) in supervised learning to predict COVID-19 death cases while improving prediction accuracy. The model's performance was evaluated using accuracy alongside precision and recall, along with F1-score metrics that validated its operational effectiveness for the healthcare research foundation.

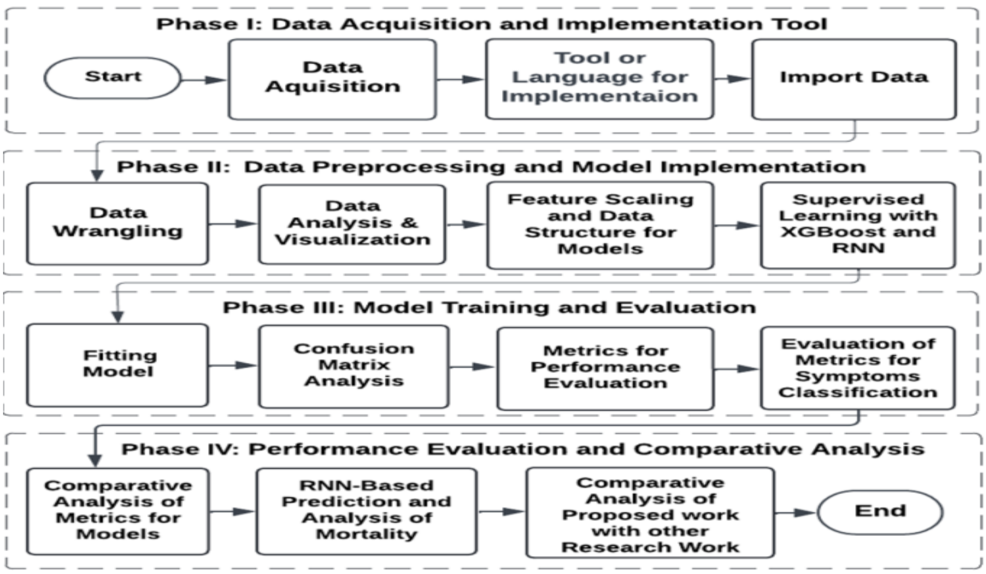

Figure 1: Proposed work's block diagram

Algorithm 01: Optimized COVID-19 Mortality Prediction
Input: COVID-19 Symptoms Dataset from Kaggle Output: Model Performance Metrics and Comparative Analysis
Step 1. Data Acquisition and Preprocessing *// Load the dataset containing COVID-19 symptoms, mortality rates, and other relevant data.* *1.1. COVID19_dataset ← LoadDataset("Kaggle/COVID19_Symptoms")* *// Extract relevant features (e.g., symptoms, confirmed cases, mortality rates).* *1.2. features ← ExtractFeatures(COVID19_dataset)* *// Clean the dataset by removing null values, duplicates, and irrelevant information.* *1.3. clean_data ← CleanData(features)* *// Perform normalization or scaling on the dataset for consistency in model training.* *1.4. norm_data ← NormalizeData(clean_data)* *// Split the dataset into training and testing sets.* *1.5. train_data, test_data ← SplitDataset(norm_data, train_size)* ***Step 2. Data Visualization*** *// Visualize the distribution of key symptoms to understand the dataset better.* *2.1. symptom_distribution_plot ← PlotSymptomDistribution(train_data)* *// Generate a heatmap to visualize correlations between symptoms and mortality rates.* *2.2. correlation_heatmap ← PlotCorrelationHeatmap(train_data)* *// Plot the time series of daily mortality rates.* *2.3. mortality_trend_plot ← PlotMortalityTrend(train_data)* ***Step 3. Supervised Learning with RNN and XGBoost*** *// Initialize the Recurrent Neural Network (RNN) model for time-series analysis.* *3.1. rnn_model ← InitializeRNN()* *// Train the RNN model using the training dataset.* *3.2. trained_rnn_model ← TrainRNN(rnn_model, train_data)* *// Initialize the XGBoost model for feature-rich data analysis.* *3.3. xgboost_model ← InitializeXGBoost()* *// Train the XGBoost model with data augmentation techniques.* *3.4. trained_xgboost_model ← TrainXGBoost(xgboost_model, train_data)* *// Combine the predictions of RNN and XGBoost for enhanced accuracy.* *3.5. combined_predictions ← CombineModels(trained_rnn_model, trained_xgboost_model, test_data)* ***Step 4. Model Evaluation*** *// Evaluate the performance of the combined model using test data.* *4.1. performance_metrics ← EvaluateModel(combined_predictions, test_data)* *// Calculate accuracy, precision, recall, and F1-score.* *4.2. accuracy, precision, recall, f1_score ← CalculateMetrics(performance_metrics)* *// Generate a confusion matrix to assess the classification performance.* *4.3. confusion_matrix ← GenerateConfusionMatrix(performance_metrics)* ***Step 5. Comparative Analysis and Discussion*** *// Compare the proposed model's accuracy with existing models in the literature.* *5.1. accuracy_comparison ← CompareAccuracy(trained_models, existing_models)* *// Identify areas of significant improvement over past methods.* *5.2. improvement_areas ← IdentifyImprovements(trained_models, test_data)* *//Discuss the implications of the findings and potential applications in healthcare.* *5.3. implications ← DiscussImplications(improvement_areas, accuracy_comparison)* **Step 6.** ***End***

2.1. Phase I: Data Acquisition and Implementation Tool

2.1.1. Data Acquisition

The "COVID-19 Symptoms Dataset" from Kaggle serves as our primary research material because it contains extensive information about patient symptoms and death statistics, as well as mortality rates, along with confirmed cases. The dataset contains four major COVID-19 symptoms, including sore throat alongside high fever and dry cough with breathing problems. As an expansive open-source resource, it provides solutions for real-world COVID-19 issues [45]. This dataset includes Government of India observational data containing symptoms spanning multiple days and remains available for enhancement. Our main reason for choosing this dataset was to discover vital COVID-19 indicator symptoms, alongside improving forecasting precision for mortality rates [46].

2.1.2. Tool or Application for Implementation

Our research solution to be demonstrated utilizes Python for its simplicity, effectiveness, and readability, using a small amount of code to carry out data analysis, machine learning, deep learning, and robotics. Utilization of Python across the globe in data science and AI renders it the perfect choice. Experimental base selection and choice of programming language are the starting points. The open-source web-based platform, Jupyter, is used in its development. Python is the most adaptable data science programming language. Its multidisciplinary application includes AI and data analysis, making it a core part of computational operations, demanding flexibility, scalability, and good community support.

2.1.3. Importing Required Libraries

The XGBoost and RNN algorithms are implemented within the Anaconda Jupyter Notebook environment through Python. Our application utilizes Seaborn alongside Matplotlib for visual data displays, Pandas for tabular management, and NumPy as a numerical computation tool. These libraries strengthen the results by improving performance and numerical analysis alongside data processing and visual interpretation capabilities.

Machine learning subsets undergo successive training on the XGBoost model, which constructs an ensemble framework through weight adjustment based on its performance ratings. The RNN model improves prediction precision by maintaining a memory of former inputs along with detecting timing patterns found within ordered data sequences. Combined use of these models brings about an extensive procedure for mortality diagnosis.

The dataset is randomly divided into training and testing sets using an 80:20 split. Stratified sampling is employed to ensure balanced representation of mortality outcomes in both sets. This split is used consistently for training the XGBoost and RNN models to maintain reproducibility and fairness in model evaluation.

2.2. Phase II: Data Processing and Model Implementation

2.2.1. Data Wrangling and Pre-Processing

Data processing begins by cleaning and pre-processing data to eliminate unneeded information that includes missing values, outliers, and inconsistencies before model development. Much time is required for completing this data preparation stage. The implementation of effective wrangling leads to clean datasets without errors. Various preprocessing methods helped us to manage repetitive data while resolving data gaps as well as duplicate values.

The dataset visualization in Figure 2 uses heat mapping to present the data points by showing present values in red areas while empty spaces represent missing information.

The "COVID-19 Symptoms Dataset" used in our study is examined for missing values using a heatmap visualization (see Figure 2). Our preprocessing confirmed that the dataset is complete, with no missing values in key features such as dry cough, high fever, sore throat, and breathing difficulty. Duplicate and inconsistent entries are removed during the cleaning phase. Regarding outliers, feature scaling techniques are applied—namely normalization for RNN input and standardization for XGBoost—to reduce the influence of extreme values and ensure stable model performance.

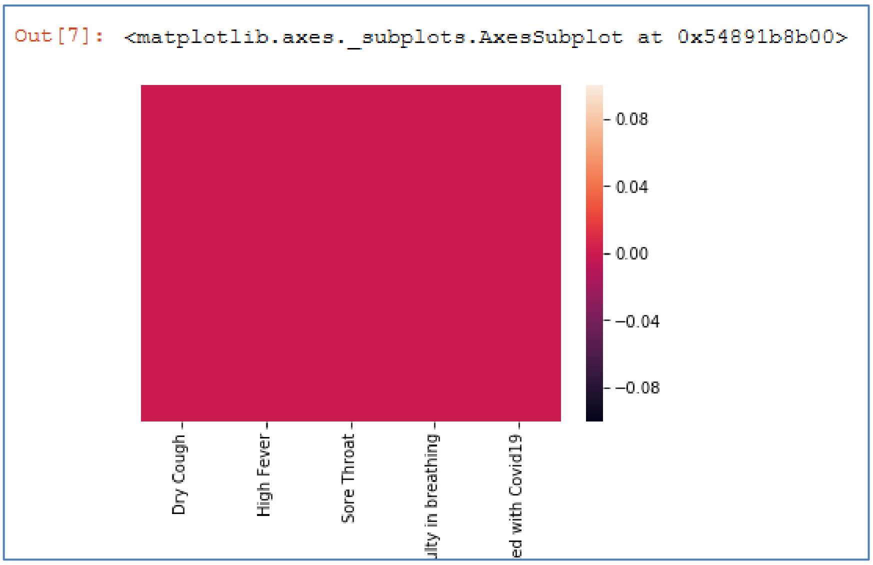

Figure 2 : Heatmap of Missing Values in COVID-19 Symptom Data

The Display demonstrates a completely red color pattern that shows no missing data in Dry Cough, High Fever, and COVID-19 infection status features. The data analysis readiness is supported by this result. No missing values appear in the dataset, which demonstrates successful completion of our data cleaning process to produce a high-quality resource for modeling purposes.

A clean dataset appears in Figure 3 since these efforts successfully eliminated missing data and duplicates that are ready for analysis.

```
Out[4]: Dry Cough                0
        High Fever               0
        Sore Throat              0
        Difficulty in breathing  0
        Infected with Covid19    0
        dtype: int64
```

Figure 3 : Heatmap illustrating the Absence of Missing Values in the Preprocessed Symptom Dataset

2.2.2. Data Analysis

The analysis phase uses descriptive statistics and visualizations together with correlation analysis. Tables 1 and 2 present the dataset that contains confirmed cases, deaths, and mortality rates for each country. XGBoost and RNNs serve to enhance death prediction for COVID-19 patients. The models detect symptom patterns that help enhance mortality prediction. XGBoost and RNNs function together to enhance the prediction of COVID-19 death cases based on the information in Tables 1 and 2.

Table 1 : Symptom Frequencies and COVID-19 Infection Status

Dry Cough	High Fever	Sore Throat	Difficulty in Breathing	Infected with COVID-19
0	2	3	0	No
15	15	20	16	Yes
4	5	0	0	No
4	7	9	10	No
0	0	1	0	No
6	0	6	0	No
16	17	18	16	Yes

The statistics related to COVID-19 in the USA states are presented through Table 2, which includes confirmed cases, deaths, recoveries, mortality ratio, together with geographical coordinates. The results show that California contains 796,436 confirmed virus cases at 1.92% mortality, while Alaska reported the lowest statistics. The proposed solution combines RNNs with XGBoost methods to enhance the accuracy of mortality predictions from symptoms, together with other vital characteristics. These models offer better global prediction capabilities while enabling users to identify patterns that strengthen their accuracy.

Table 2 : COVID-19 Mortality Ratio and Statistics by U.S. State

State	Confirmed Cases	Death s	Recovere d	Mortality Ratio	Latitude	Longitude	USA State Code
Alabama	147153	2488	0	1.69	32.318231	-86.902298	AL
Alaska	7004	45	0	0.64	63.588753	-154.493062	AK
Arizona	215284	5525	0	2.57	34.048928	-111.093731	AZ
Arkansas	77963	1229	0	1.58	35.20105	-91.831833	AR
California	796436	15291	0	1.92	36.778261	-119.417932	CA

The state of California has the greatest reported COVID-19 cases at 796,436, and Alaska demonstrates the fewest infections among the states. XGBoost machine learning algorithms connected to RNNs in deep learning models will enhance the precision of COVID-19 death risk assessment. The algorithm accesses data patterns to assist pandemic administration tasks while generating worldwide forecasting methods

2.2.3. Data Visualization

Our data visualization effort serves to identify patterns and anomalies only after we finish data cleaning and achieve a better understanding of variable relationships. A visual representation of the dataset uses Matplotlib as a plotting library tool to help select algorithms by enhancing data visibility.

Figure 4 shows the number of COVID-19 deaths over 50 days within the studied period. The data shows increasing and decreasing trends, which lead to the pattern of decreasing mortality rates.

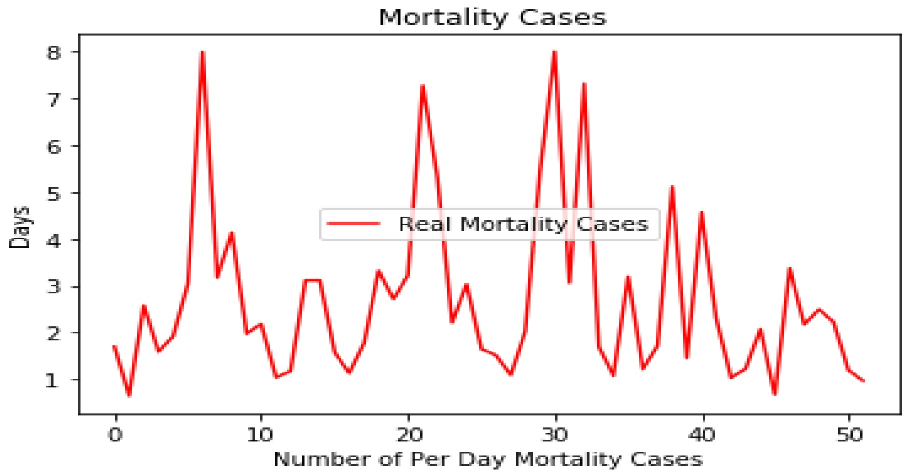

Figure 4: Daily Mortality Cases Over 50 Days

Public health efforts decrease mortality rates, but the reason for any change in death rates stems from both variations in viral genetics and intervention programs. The visual representation of data through displays leads users to identify invisible patterns, which enable them to choose better options. The deep learning model for regression will start generating mortality predictions after completing accuracy tests on predicted results.

2.2.4. Feature Scaling and Data Structure for XGBoost and RNN

Both XGBoost and RNNs receive processed COVID-19 Kaggle data with feature scaling and data structuring applied

- *Feature Scaling for XGBoost and RNNs*

Feature scaling is a type of preprocessing in machine learning that adjusts or standardizes data in order to ensure that no one feature dominates more than the other in a model's predictions and provides a value range for every feature.

Feature scaling is important in the ensemble learning technique called XGBoost model because feature scaling improves convergence and reduces bias to a feature that has a big range. A common type of scaling is standardization, which adjusts features to have zero mean and unit variance. It does so by adjusting crucial symptoms, for instance, fever and dry cough, while doing away with bias in prediction to enhance accuracy. Scaling improves model performance in the COVID-19 dataset that consists of symptoms and mortality cases.

Feature scaling is important to RNNs, especially for time-series data like the development of COVID-19 symptoms. Normalization (scaling of features to the range 0 to 1) guarantees that input features, e.g., symptoms and mortality, have similar ranges to prevent uneven weightage of larger values. Scaling appropriately keeps gradients stable in back propagation and facilitates effective learning and temporal relationships to make precise predictions.

- *Data Structure for XGBoost and RNNs*

The data is now arranged in a more machine learning-compatible fashion, defining how to store, access, and process the data for efficient model operation and training.

Much like the rest of the disease associated data, information related to COVID-19 comes in form of data sheets. Patients are recorded in rows, and symptoms like sore throat, breathing difficulty, fever, dry cough, and death are captured in the columns. That format will also enable XGBoost to apply Boosting's algorithms for better predictions.

For RNNs, the data is geared to account for the ordered characteristic of time series data, especially with respect to worsening symptoms for each patient. The system, as an RNN, makes predictions about dire symptoms appearing or death based on the dire symptoms that are fed into the system over time. The model is trained using feature scaling and data structuring for XGBoost algorithms and RNNs in the accuracy optimization context for COVID-19 death prediction and general accuracy optimization. This performance is systematically improved by increasing the accuracy in the prediction of COVID-19 death trends.

2.2.5. Supervised Learning with XGBoost and RNN Models

In ML and AI, supervised learning is a fundamental concept that uses labelled data to train models to make predictions on unseen data, specifically regression and classification problems. XGBoost and RNNs are used for this purpose [47].

Building decision trees individually, XGBoost is great for high dimensional spaces like fraud and spam detection. RNNs are great for NLP and time series problems because they are designed to process sequential data and keep hidden states to preserve temporal relationships. In the spirit of power, advanced RNN variants that address vanishing gradients are GRUs and LSTM networks. All these show how versatile supervised learning is[48].

- *XGBoost Classifier*

XGBoost (Extreme Gradient Boosting) is a supervised ensemble learning model that can handle big datasets. It combines weak learners (mostly decision trees) iteratively to correct previous errors until it reaches the desired accuracy. Requires labeled datasets, XGBoost finds important features that affect the predictions, and is good in feature rich scenarios. Its applications are in classification tasks like spam detection, fraud detection, and Kaggle competitions, where precision is key [49]. XGBoost's performance and feature importance make it useful in many predictive modeling scenarios.

The XGBoost model is optimized for feature-rich data analysis using hyperparameters selected through grid search. Key parameters include a learning rate of 0.01, a maximum depth of 6, 200 estimators, a subsample ratio of 0.8, and a colsample_bytree value of 0.9, with the objective set to binary logistic classification. Early stopping is applied if the validation log-loss does not improve for 50 rounds, and model performance is evaluated using 5-fold cross-validation.

- *Recurrent Neural Network (RNNs)*

Recurrent neural networks (RNNs) are specialized neural networks for sequential input and are good at tasks like time series analysis, natural language processing (NLP), and sequence based predictions. When predicting COVID-19 mortality, RNNs effectively model the temporal dependencies between symptoms and death for the Kaggle COVID-19 dataset study. The data include symptoms such as sore throat, difficulty in breathing, fever, dry cough, etc. RNNs maintain a hidden state to recall the past inputs and are suitable for pattern recognition in mortality prediction. The RNN structure is defined by an input layer that takes sequential symptoms (X1, X as in Figure 5), hidden layers that select features, intermediate layers that are output to other hidden layers, and an output layer that gives as output the final prediction (Y in Figure 5).

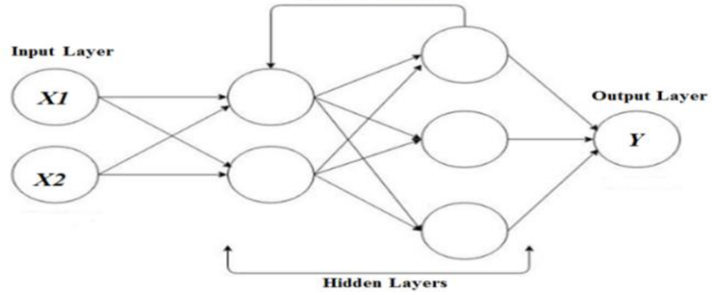

Figure 5: Predicting COVID-19 mortality using a Recurrent Neural Network (RNN).

Vanishing or inflating gradients are problems for conventional RNNs. These are addressed by sophisticated topologies such as Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) networks, which enhance long-term sequence learning [50].
The LSTM model is configured with 2 layers, each containing 64 hidden units and using the ReLU activation function. A dropout rate of 0.2 is applied to prevent overfitting. The model is optimized using the Adam optimizer with a learning rate of 0.001, and it employs Mean Squared Error (MSE) as the loss function. Training is performed with a batch size of 32 over a maximum of 100 epochs, with early stopping enabled to halt training if the validation loss does not improve for 10 consecutive epochs (patience = 10).

3. Results and Discussion

Confusion matrix analysis is used to validate the RNN and XGBoost models in this section, and performance metrics, highlighting superior accuracy over prior research, enabling reliable predictions, and improving healthcare resource allocation and decision-making.

3.1. Phase III: Model Training and Evaluation

3.1.1. Fitting Model

The Kaggle COVID-19 Pipeline gives detailed data on the confirmed cases, death ratio, and in-depth understanding about patient symptoms, etc. These symptoms are important because they indicate potential mortality cases: dry cough, fever, sore throat, and difficulty breathing. The dataset is separated into the training and test sets to ensure it represents the real world. An iterative approach in an optimization technique changes model parameters based on error signals for improving the classification accuracy and reducing errors. RNN-based deep learning combined with XGBoost is another machine learning model that takes the benefits of these methods. Performance is evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis, thus offering an in-depth assessment of the model's ability to predict COVID-19 death cases.

3.1.2. Confusion Matrix Analysis

A confusion matrix evaluates the accuracy of a classification model as well as its error types. It offers information on model enhancement and medical interpretation misclassifications, and detects false positives (FP) and false negatives (FN). The matrix helps to increase diagnostic accuracy. Machine learning evaluation of model performance depends in part on visualizing the different errors and computing the accuracy. Comparing actual with predicted labels helps to fine-tune the model. True Negatives (TN), False Negatives (FN), True Positives (TP), and False Positives (FP) are displayed in the confusion matrix of our model in Figure 6.

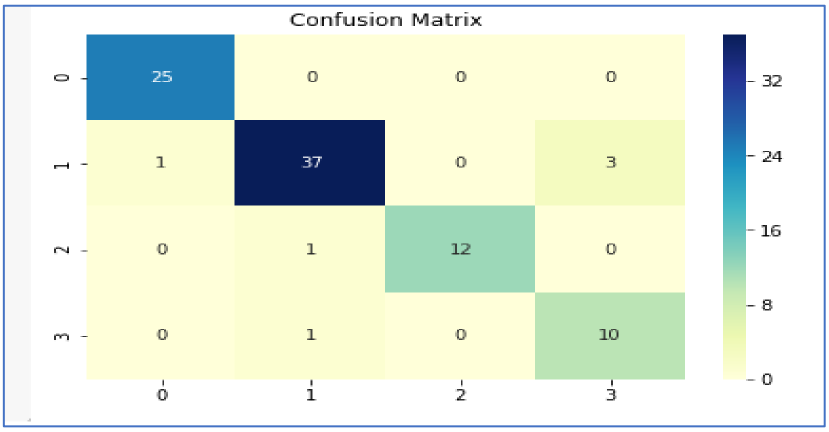

Figure 6 : Recurrent Neural Network (CNN)-Generated Confusing Matrix corresponding to our model

Among the elements are True Positives (TP)—correctly projected positive occurrences—True Negatives (TN)—correctly projected negative instances—False Negatives (FN), which are incorrectly predicted as negative, and False Positives (FP), which are inaccurately predicted positive.
Definitions for True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are expanded for each class in the multi-class confusion matrix (Figure 6). These measurements are averaged across all classes to generate macro-averaged values: Macro-Averaged TP = 21 (average correct positive predictions), Macro-Averaged TN = 63 (average correct negative predictions), Macro-Averaged FP = 1.5 (average incorrect positive predictions), and Macro-Averaged FN = 1.5 (average incorrect negative predictions). Model accuracy and performance metrics, including recall, accuracy, and precision, are computed from these elements for a thorough performance assessment.

3.1.3. Key Metrics for Performance Evaluation of COVID-19 Prediction Models

The proposed research evaluates the performance of XGBoost (ML) and Recurrent Neural Networks (RNNs, DL) using a Kaggle COVID-19 dataset containing patient symptoms (dry cough, high fever, sore throat, difficulty in breathing), mortality rates, and confirmed cases. These features are essential for identifying key symptoms and predicting COVID-19 case severity.
Performance is assessed using key metrics—accuracy, precision, recall, and F1 score through 10-fold cross-validation to ensure robust evaluation. Accuracy (AC) measures the proportion of correctly classified cases, calculated as

$$AC = \frac{TP + TN}{TP + FN + TN + FN} \tag{1}$$

Precision (PR) calculates the proportion of true positives among all positive predictions,

$$PR = \frac{TP}{TP + FP} \tag{2}$$

Recall (RE) measures the percentage of actual positives correctly identified,

$$RE = \frac{TP}{TP + FN} \tag{3}$$

The F1 score balances precision and recall,

$$F1 - Score = 2 \times \frac{PR \times RE}{PR + RE} \tag{4}$$

These metrics, derived from confusion matrices averaged across all cross-validation folds, provide comprehensive insights into the models' classification performance. Advanced data processing techniques such as augmentation and dimensionality reduction are used to improve prediction accuracy for COVID-19 death cases. This rigorous evaluation emphasizes the models' effectiveness in enhancing predictions and their potential to contribute to healthcare outcomes. By leveraging XGBoost and RNN models with cross-validation, the research demonstrates reliable COVID-19 mortality predictions with quantified stability, offering valuable insights for pandemic management.

3.1.4. Evaluation of Metrics for COVID-19 Symptoms Classification

Using accuracy, F1-Score, recall, and precision for dry cough, fever, sore throat, and breathing difficulty, this section examines how well proposed models classify COVID-19 symptoms (Table 3).

Table 3: Performance Metrics of Proposed Models for COVID-19 Symptoms Classification

Features	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Dry Cough	96	100	98	98
High Fever	95	90	92	94
Sore Throat	100	92	96	99
Difficulty in Breathing	77	91	83	95

With the model guaranteeing few false negatives and accurate forecasts, 96 percent precision, 100 percent recall, and 98 percent F1 Score and accuracy for predicting dry cough symptoms, it exhibits excellent accuracy and recall. For high fever, precision is 95%, and recall is 90%, yielding a 92% F1-Score and 94% accuracy, though some cases may be missed. Sore throat symptoms are detected with 100% precision, 92% recall, 96% F1-Score, and 99% accuracy, showing strong performance in identifying these symptoms. Difficulty in breathing shows lower precision (77%) but high recall (91%), with an F1-Score of 83% and accuracy of 95%, indicating occasional misclassification. The XGBoost and RNN models show solid performance in predicting COVID-19 symptoms, though performance for high fever and difficulty in breathing reveals room for improvement. The Kaggle dataset, used for evaluation, contains patient symptom data, including dry cough, high fever, sore throat, and difficulty in breathing, contributing to the objective of enhancing COVID-19 death prediction accuracy through XGBoost and RNN techniques. Despite strong performance, variability in results suggests potential improvements in future model refinements.

3.2. Phase IV: Performance Evaluation and Comparative Analysis

For evaluating COVID-19 mortality prediction based on patient symptoms, the accuracy, precision, recall, and F1-Score obtained from the confusion matrix are used to evaluate the performance of the proposed models.

3.2.1. Comparative Analysis of Metrics for Models in Predicting COVID-19 Mortality

A performance comparison of the XGBoost and RNN models for COVID-19 mortality prediction is shown in Table 4, with an emphasis on accuracy, precision, recall, and F1 Score measures.

Table 4 : Overall Performance Comparison of Models for Predicting COVID-19 Mortality

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
XGBoost	88.47 ± 1.2	89.67 ± 0.9	87.37 ± 1.1	88.42 ± 1.0
RNN	94.00 ± 0.8	92.00 ± 0.7	93.00 ± 0.9	92.00 ± 0.8

To ensure the robustness of our models, we employed 10-fold cross-validation for both XGBoost and RNN. The results demonstrated consistent performance across all folds. For the XGBoost model, the mean accuracy was 88.47% (±1.2%), precision was 89.67% (±1.1%), recall was 87.37% (±1.3%), and F1-score was 88.42% (±1.0%). The RNN model achieved a mean accuracy of 94.0% (±0.8%), precision of 92.0% (±0.9%), recall of 93.0% (±0.7%), and F1-score of 92.0% (±0.8%). The low standard deviations indicate stable and reliable performance, reinforcing the effectiveness of our proposed approach in predicting COVID-19 mortality.

With the XGBoost model, one achieves 88.47% accuracy, 89.67% precision, 87.37% recall, and 88.42% F1 score. Given their accuracy in correctly identifying positive cases and their recall catching most true positives, these data show excellent performance. Still, slightly less recall compared to the model of the recurrent neural network (RNN) points to a trade-off. The RNN model outperforms XGBoost with 92% accuracy, 93% recall, 92% F1 score, and 92%

precision. Its better performance shows that RNN is especially good at spotting and recording good cases, therefore providing the most precise model for COVID-19 death forecast.
The Table 4 findings indicate XGBoost as well as RNN models accurately forecast COVID-19 mortality, with RNN surpassing in all assessed dimensions. RNN's outstanding precision and recall underline its capability to find actual positives, which is quite important for a precise death forecast. This performance is driven by the ability of RNN to spot chronological relationships in sequence data. Though XGBoost provides a well-rounded approach, it has slightly lower recall, therefore possibly missing some real positives. These distinctions underline the need to choose models according to particular objectives, such as maximizing recall in death forecasts. Using XGBoost together with RNN leverages the advantages of each approach to achieve better forecast accuracy and medical results.

3.2.2. RNN-Based Prediction and Analysis of COVID-19 Mortality: Predicted vs. Real Cases

This section deals with using Recurrent Neural Networks (RNNs) to forecast COVID-19 fatal outcomes. Results in Figure 7 project RNNs, an important deep learning technique, as being crucial in forecasting complex data set trends.

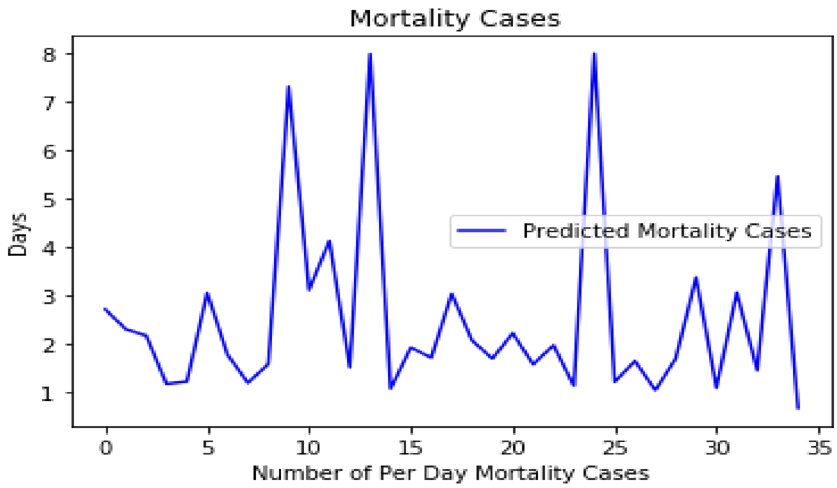

Figure 7 : Predicted Mortality Cases

- *Analyzing Predicted Mortality Cases:*

The predicted cases are represented as a blue line in Figure 7, with predicted death cases on the y-axis and the prediction period (days) on the x-axis. An expected pattern of cyclical deaths can be representative of seasons of disease spread or public health and surgical response variation. Mortality is altered due to dynamic forces of disease transmission and treatment availability, limiting model accuracy. As opposed to pervasive patterns, outliers are abrupt bulges or breaks, whose improvements model-wise have to be made through architectural or feature addition. The accuracy of a model depends on training data quality; errors or biases require tight data cleansing and validation. Public health policy and socio-economic status externalities influence mortality rates and must be investigated. While the recurrent neural network (RNN) suggests that it must be improved for predictive precision.

- *Analyzing Real and Predicted Mortality Cases*

Figure 8 illustrates the model's performance by comparing the observed daily death counts with the predicted numbers over time. The x-axis represents the progression of days, while the y-axis depicts the daily death count. The blue line indicates the model's predictions, whereas the red line represents the actual reported death figures. This side-by-side visualization highlights how well the predictions align with real-world outcomes and serves as a key measure of the model's performance.

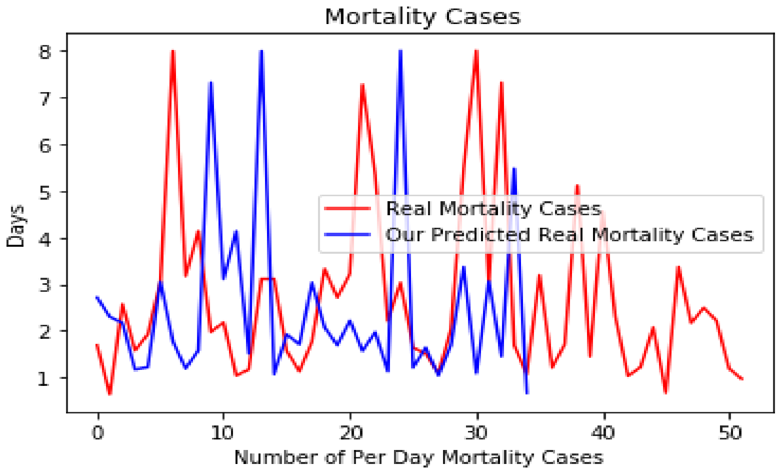

Figure 8 : Real and Predicted Mortality Cases.

The correlation of projected and actual instances of mortality shows that the model is indeed reflective of patterns of mortality over time. As actual mortality levels change, the projections adapt as well, showing that the model can identify patterns needed to project future instances.

Short-term changes in real and predicted mortality rates are caused by infection rates, treatment, and testing differences. Sensitive response of the model to them improves prediction accuracy in dynamic pandemic settings. The existence of moderate correlation and some deviations indicates improvement areas. Closing these gaps is required to further improve performance and reliability.

Gaps can occur due to the hidden variables, i.e., unforeseen changes in healthcare or regulations, and data quality issues like imprecision or skewness. Other attributes like demographics (age, sex, comorbidities), healthcare access (ICU beds and ventilators availability), and environmental data (air, temperature) must be included in the model.

Application of architectures such as Gated Recurrent Units or Long Short-Term Memory and hyperparameter optimization, such as learning rate, batch size, and number of layers, would enhance performance. The quality of data, by eliminating outliers and filling missing values, is essential to create a sane mortality prediction model.

3.2.3. Comparative Analysis of Proposed Work with Other Research Work

The comparative analysis of our proposed work with existing research highlights the performance improvements achieved using advanced machine learning techniques. The analysis is based on the accuracy scores reported in Table 5 and Figure 9, which includes research by Husnul Khuluq, et al. [36] and Xiangao Jiang, et al. [5] and our proposed work using XGBoost and Recurrent Neural Networks (RNNs).

In addition to comparing our proposed models with recent research, we have extended our analysis to include performance comparisons with traditional machine learning algorithms such as Logistic Regression (LR) and Multilayer Perceptron (MLP), a standard feed forward neural network.

Table 4 : Comparative Analysis of the Proposed Work in Relation to Other Research Work

Research Work	Data Set	Algorithm	Accuracy Score (%)
Husnul Khuluq, et al. [36]	Covid-19	KNN	75
		Naive Bayes	77
		Logistic Regression	81
		Random Forest	81
		SVM	81
		Decision Tree	79
Xiangao Jiang, **et al. [5]**	Covid-19	Logistic Regression	50
		KNN (k=5)	80
		Decision Tree (based on Gain Ratio)	70
		Decision Tree (based on Gini Index)	70
		Random Forests	70
		Support Vector Machine	80
Our Proposed Work	Covid-19	XGBoost	88.47
		RNN	94

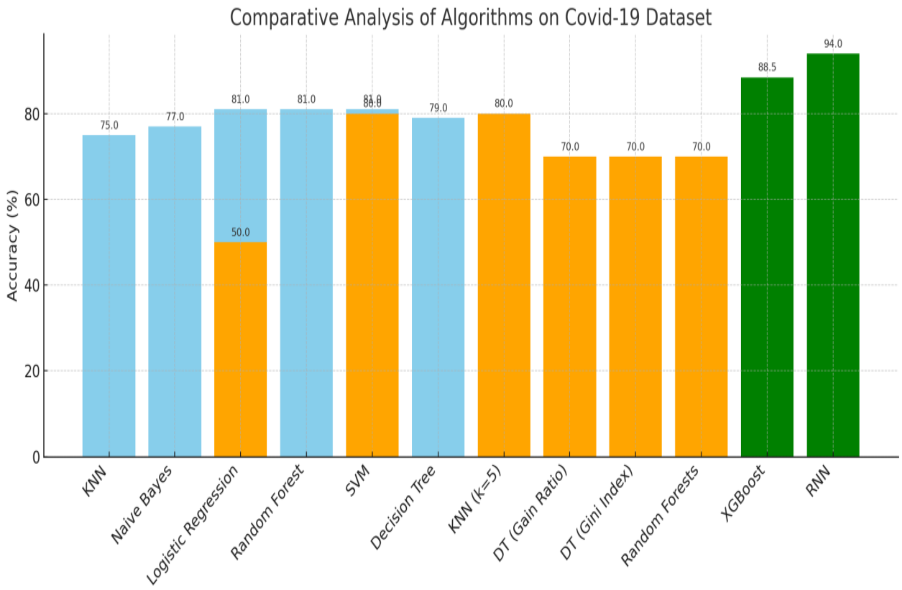

Figure 9: Comparative Analysis of the Proposed Work in Relation to Other Research Work

Khuluq Husnul et al., examine the application of machine learning (ML) techniques for COVID-19 patient mortality prediction using a Kaggle dataset. The six machine learning algorithms that were evaluated were KNN, Naive Bayes, SVM, Decision Tree, Random Forest and Logistic Regression. Important indicators of mortality were found with particular attention paid to the significance of symptoms in forecasting mortality from COVID-19. The study comes to the conclusion that the suggested approach helps frontline physicians make prompt clinical decisions because it is easily updated with new data. They evaluated several algorithms using a COVID-19 dataset. Their findings showed that SVM, Random Forest, and Logistic Regression all attained 81 percent accuracy. However, the accuracy of the KNN and Decision Tree models was lower at 75% and 79%, respectively. These findings demonstrate the superiority of ensemble methods such as Random Forest and SVM over simpler models like Decision Trees and KNN.

Jiang Xiangao et al., examined a number of algorithms on a COVID-19 dataset, such as the conventional Support Vector Machine (SVM), Random Forests, Decision Trees, K-Nearest Neighbors (KNN), and Logistic Regression, which are kinds of machine learning models. An accuracy of 50% was achieved using logistic regression. This decreased accuracy highlights its inefficiency in comparison to more sophisticated models since it is unable to handle complex non-linear relationships in the data. With an accuracy of 80%, K-Nearest Neighbors (k=5) demonstrated its ability to handle non-linear data. Its simplicity, however, also increases the risk of overfitting, which weakens it in comparison to more complex models. Gain Ratio and Gini Index decision trees both attained a 70% accuracy rate. Despite producing results that are easy to understand, decision trees' performance indicates that they might not fully capture the dataset's complexity. Their accuracy scores consistency indicates a limited but steady level of efficacy. A 70% accuracy rate was also attained by Random Forests, demonstrating an improvement over single decision trees. Despite its effectiveness, this approach is still inferior to more sophisticated ones. Its 80% accuracy rate showed that the SVM could handle high-dimensional data. However, it still performs worse than more sophisticated algorithms.

- *Contributions of the Proposed Work*

Conversely, our suggested work employs advanced methods to demonstrate appreciable gains in prediction accuracy at 88.47%. XGBoost performed 47 percent better than every algorithm that Jiang et al. evaluated for accuracy. Its high performance demonstrates XGBoost's resilience and efficacy in handling complex datasets. Through iterative error correction and boosting, the sophisticated ensemble learning algorithm XGBoost combines several weak learners to produce a powerful prediction model. With an accuracy of 94%, RNNs achieved the highest accuracy. This remarkable outcome shows how effective deep learning methods, especially RNNs, are at capturing the intricacies of the COVID-19 dataset. RNNs perform exceptionally well with sequential data and time-series forecasting, making them especially well-suited for long-term trend prediction. The RNN model's accuracy shows how well it can detect temporal patterns and dependencies.

- *Performance Comparisons with Traditional Models*

Table 5 shows that Logistic Regression (LR) achieved an accuracy of 50% in the study by Jiang et al. [5] and 81% in the study by Khuluq et al. [35]. While these scores reflect some predictive utility, LR's linear structure limits its capacity to model complex, nonlinear interactions commonly found in COVID-19 datasets. In contrast, our models achieved substantially higher accuracy: XGBoost reached 88.47%, and RNN attained 94%, demonstrating a marked improvement in predictive performance.

Multilayer Perceptron (MLP), a traditional neural network model, was evaluated by Khuluq et al. [35] and reported an accuracy of 81%, comparable to that of SVM and Random Forest. However, MLP lacks the ability to process sequential data effectively. In comparison, our RNN model, designed to handle time-series inputs, yielded an accuracy of 94%, outperforming MLP by 13 percentage points.

- *Analysis of Model Strengths and Limitations*

XGBoost consistently outperformed traditional models like LR, Decision Trees, and KNN, offering 7.47–38.47 percentage points higher accuracy. This performance boost is attributed to its gradient boosting framework, which efficiently handles feature interactions and class imbalances.

RNNs excel in analyzing temporal dependencies, which are critical in modeling symptom progression in COVID-19. Their ability to retain information across time steps allows them to better model real-world clinical timelines compared to Traditional Neural Networks (MLPs), which treat inputs as independent features.

- *Justification for Model Selection*

The comparative results underscore the rationale for selecting XGBoost and RNN as the core components of our hybrid framework: XGBoost provides high accuracy in tabular data tasks, along with interpretable feature importance rankings. RNN offers strong capabilities in modeling sequential data, making it ideal for predicting outcomes from time-evolving symptoms.

These findings not only confirm the superior performance of our models but also establish their practical relevance in COVID-19 mortality prediction, as they significantly outperform baseline machine learning techniques.

- *Implications and Contributions*

Our research demonstrates significant advancements in traditional machine learning methods. The XGBoost and RNN models achieve notably higher accuracy than traditional algorithms. The RNN model, with its 94% accuracy, shows substantial improvement in prediction capabilities, providing more reliable outcomes compared to existing methods.

Utilizing XGBoost and RNNs represents a considerable advancement over simpler methods. XGBoost's ability to manage large datasets and complex relationships, combined with RNNs' proficiency in sequential data analysis, significantly enhances performance.

- *In-Depth Analysis of the Findings*

Our study advances the field of COVID-19 mortality prediction by integrating XGBoost and Recurrent Neural Networks (RNNs), achieving superior accuracy (94% for RNNs and 88.47% for XGBoost) compared to traditional machine learning methods. These results align with the growing recognition of deep learning and ensemble techniques in handling complex, non-linear relationships in medical datasets. Specifically, the RNN's ability to capture temporal dependencies in symptom progression significantly enhances prediction accuracy, addressing a critical limitation of prior studies that relied on static models like Logistic Regression or Decision Trees. This contribution is particularly relevant given the dynamic nature of COVID-19 symptoms and their evolution over time.

- *Unexpected or Contradictory Outcomes*

While our findings generally support the superiority of advanced models, the notably low accuracy of Logistic Regression (50%) in Jiang et al.'s study contrasts with its moderate performance (81%) in Khuluq et al.'s work. This discrepancy may stem from differences in dataset composition or pre-processing. For instance, Jiang et al.'s dataset might lack key features or exhibit higher imbalance, exacerbating Logistic Regression's limitations in handling non-linear patterns. Our results, however, consistently demonstrate that XGBoost and RNNs mitigate these issues through robust feature handling and sequential data analysis, respectively.

This study contributes to the field in several significant ways. Methodologically, it bridges traditional machine learning and deep learning by combining XGBoost's feature importance analysis with the temporal modelling capabilities of RNNs, offering a more comprehensive approach to mortality prediction. The high accuracy achieved by our models holds practical implications for enhancing clinical decision-making and optimizing resource allocation, especially in settings where timely intervention is crucial. Additionally, our use of a rich, symptom-focused dataset highlights the value of integrating diverse clinical features, setting a precedent for future research in health crisis management. To strengthen these contributions, we recommend further validation using larger, multi-center datasets and hybrid model exploration. Incorporating demographic variables and addressing data collection biases will also enhance the models' robustness and generalizability across varied clinical environments..

- *Practical Applications*

The proposed model, integrating XGBoost and Recurrent Neural Networks (RNNs), offers promising practical applications in real-world healthcare settings, particularly in managing the COVID-19 pandemic. One major application lies in hospital resource allocation, where the model can predict patient mortality risks, helping healthcare facilities prioritize critical resources like ICU beds and ventilators for high-risk individuals. Additionally, the model supports early intervention strategies by identifying patients likely to experience severe outcomes, enabling timely medical responses that may reduce mortality rates. At a broader level, public health agencies can use the model to forecast mortality trends across regions, facilitating more efficient distribution of medical supplies and informing vaccination strategies. Moreover, its integration into telemedicine platforms can assist in remote triage, guiding patients toward appropriate care levels based on their predicted risk.

- *Challenges and Limitations in Model Implementation*

However, several challenges may hinder implementation. The model's effectiveness depends on the availability of high-quality and complete datasets, which may not be consistent in real-world settings. Integration with existing hospital systems, especially electronic health records (EHRs), could pose technical difficulties. Ethical concerns regarding data privacy require adherence to strict regulations, while the black-box nature of RNNs and XGBoost may affect clinician trust. Furthermore, the model must be updated regularly to remain effective against evolving COVID-19 variants.

Our research employs a comprehensive COVID-19 dataset, integrating various symptoms and outcome variables. This extensive use of data improves model accuracy by considering a wide range of features and their interactions. The proposed models are optimized to address the limitations of traditional approaches. These advanced methods are efficient in producing more accurate predictions for COVID-19 mortality cases, as evidenced by the high accuracy attained. Improved accuracy in predictions has practical implications for healthcare and disease management. More accurate predictions assist in better resource allocation, timely interventions, and informed decision-making, contributing to more effective management of COVID-19.

The comparative analysis of our proposed work relative to existing research reveals notable advancements in predictive accuracy for COVID-19 mortality cases. Khuluq, Husnul et al. employed a number of traditional machine learning techniques to forecast the outcomes of COVID-19. Their study achieved decent accuracy with Logistic Regression, Random Forest, and SVM. However, these methods have limitations in capturing complex, non-linear patterns in the data. Xiangao Jiang et al. employed several algorithms, with KNN and SVM achieving the highest accuracy. However, Logistic Regression exhibited notably lower performance, indicating that simpler models may struggle with complex patterns in COVID-19 data. In contrast, our proposed approach incorporates advanced techniques, specifically XGBoost and Recurrent Neural Networks (RNNs). The results demonstrate a significant improvement in accuracy, with XGBoost achieving 88.47% and RNN reaching 94%. This enhanced performance is attributed to XGBoost's ability to handle complex interactions and RNNs' strength in bagging patterns and temporal connections throughout time. Overall, our proposed work makes substantial advancements in COVID-19 mortality prediction by using cutting-edge DL and ML methods. Compared to previous studies, these lead to improved accuracy and a better handling of intricate data patterns.

4. Conclusion and Future Work

This study proposes an enhanced approach to COVID-19 mortality rate prediction by combining machine learning and deep learning techniques. Our study uses the COVID-19 Symptoms Dataset from Kaggle, which contains extensive information on confirmed cases, mortality rates, and patient symptoms. By using Recurrent Neural Networks (RNNs) and XGBoost, the accuracy of mortality predictions has increased, and the shortcomings of previous models that mainly concentrated on clinical severity have been addressed. We used a systematic approach that included performance evaluation, supervised learning, data processing, and acquisition. Key conclusions drawn from our analysis show: The RNN model performed better than XGBoost in terms of accuracy, precision, recall, and F1-Score when predicting COVID-19 mortality. In particular, the RNNs' accuracy was 94% while XGBoosts was 88% to 47%. This improved performance demonstrates how well the RNN captures temporal dependencies and discerns true positives, both of which are essential for precise mortality prediction. Both models showed excellent performance in recognizing COVID-19 symptoms. Significantly, the RNN model performed exceptionally well in identifying symptoms like dry cough and sore throat, whereas XGBoost produced good results but a somewhat lower recall, indicating room for improvement. The accuracy of our suggested models was noticeably better than that of previous studies. In contrast to earlier research using different algorithms such as KNN, Naïve Bayes, and Logistic Regression, which reported accuracies between 50 and 81 percent, our XGBoost and RNN models obtained accuracy scores of 88 to 47 percent and 94 percent, respectively. This illustrates how prediction skills can be enhanced by sophisticated machine learning and deep learning techniques.

Additional features such as socioeconomic information, comorbidities, and immunization status should be included in future research to improve model performance. Accuracy could be increased by investigating hybrid models that combine RNNs and XGBoost. Model precision will be improved, and clinical decision-making will be supported by addressing data quality through sophisticated pre-processing, cyclical and seasonal pattern analysis, and real-world testing.

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