A Hybrid Deep Learning Framework Based on CNN-GRU-TabNet for the Predictive Modeling of COVID-19 Mortality

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ABSTRACT

The global outbreak of COVID-19 has presented substantial challenges in healthcare systems, demanding intelligent and responsive monitoring solutions. The integration of Internet of Things (IoT) technologies with Artificial Intelligence (AI) models has emerged as a promising approach to enable real-time surveillance and predictive healthcare. This study proposes an advanced hybrid deep learning model that combines Convolutional Neural Network (CNN), Gated Recurrent Unit (GRU), and TabNet for predicting COVID-19-related deaths using structured tabular data from India. The dataset comprises 4692 instances across 8 epidemiological features. The preprocessing involved mean imputation and normalization to handle missing values and scale the data. The CNN component extracts short-term temporal patterns, the GRU layer captures sequential dependencies, and TabNet applies attention-based feature refinement and selection. The model was evaluated using Mean Absolute Error (MAE), Median Absolute Error (MedAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2). The proposed CNN-GRU-TabNet model significantly outperformed traditional regression models, including Random Forest (RF), SVR, KNN, Gradient Boosting (GB), and Bayesian Ridge (BR), achieving an R^2 of 0.995 and the lowest error metrics. These results validate the effectiveness of the proposed hybrid framework for accurate and interpretable COVID-19 death prediction.

Keywords-COVID-19 mortality prediction; hybrid deep learning; IoT healthcare analytics; smart healthcare systems; CNN-GRU-tabNet

I. INTRODUCTION

The COVID-19 pandemic has disrupted healthcare systems around the world, demanding accurate forecasting tools to guide timely interventions. Modern technologies such as IoT and AI have played a vital role in tracking infections, monitoring patient health remotely, and supporting data-driven decision-making. IoT devices facilitate continuous data collection from infected individuals, while AI algorithms interpret this data to predict outcomes such as recovery, hospitalization, or mortality. In recent years, Deep Learning (DL) techniques have demonstrated promising results in various predictive healthcare tasks. However, traditional models often suffer from limitations when handling structured tabular data, especially in temporal and multivariate settings. To address these limitations, this study proposes a hybrid DL architecture that combines CNN, GRU, and TabNet to predict COVID-19 mortality using structured epidemiological data from India. The CNN layer captures localized patterns, the GRU learns long-term dependencies, and TabNet enhances interpretability through feature-wise attention. This architecture can be embedded into an IoT-enabled framework to support real-time monitoring and forecasting. The model was validated using five regression metrics to ensure robustness. To support the modeling process, the dataset underwent preprocessing, including mean imputation of missing values and normalization to improve training efficiency. The proposed CNN-GRU-TabNet model was evaluated using five standard regression metrics, namely MAE, MedAE, MSE, RMSE, and R^2, and compared against several traditional models such as Random Forest (RF), Support Vector Regression (SVR), KNN, Gradient Boosting (GB), Bayesian Ridge (BR), and Dummy Regressor (DR). The experimental results confirm the superiority of the proposed model, achieving an R^2 of 99.5, and demonstrating its effectiveness in predicting COVID-19 deaths.

Accurate prediction of COVID-19-related outcomes, such as infections and mortality, has attracted significant attention in recent years, especially with the rapid development of ML and DL techniques. Researchers have explored various data-driven approaches to support public health decision-making, enhance patient monitoring, and allocate medical resources efficiently. These efforts often rely on structured datasets enriched with demographic, epidemiological, and clinical features. In [1], the impact of temporality on the performance of ML models for COVID-19 infection and mortality was studied, using a large-scale surveillance dataset from Brazil from 2020 to 2022 and training Logistic Regression (LR) and Random Forest (RF) models on data from the same year and year-by-year. The results showed a significant decline in model accuracy when a temporal gap was present, particularly for infection prediction. Infection models experienced an average accuracy drop of 0.0256 for LR and 0.0436 for RF due to temporal drift.

In [2], ML models were used to predict the risk of mortality from COVID-19 in South Africa. This study used a retrospective dataset of 490 ICU patients and examined the impact of cross-validation, Principal Component Analysis (PCA), and synthetic minority oversampling on model performance. The deep Multilayer Perceptron (MLP) model achieved the best predictive accuracy, with an F1-score of 0.92 and an AUC of 0.94. In [3], ML models were developed to predict the progression and mortality of patients with COVID-19 and Diabetic Ketoacidosis (DKA). This study analyzed data from 242 patients at Second Xiangya Hospital and trained five ML algorithms. The LR model achieved the highest performance, with an AUC of 0.933 for predicting mortality and 0.898 for predicting severe disease progression. In addition, SHAP analysis was applied to explain the contributions of the features. In [4], an ML framework was used to predict COVID-19 case outcomes, including positive, negative, and deceased statuses. This model used a hybrid Grey-Assisted Whale Optimization Algorithm (H-GAWOA) and Adaptive Network-Based Fuzzy Inference System (ANFIS) for classification. The model was evaluated using the Johns Hopkins University dataset, showing superior predictive accuracy, particularly in death prediction, with an MSE of 0.00. In [5], two hybrid ensemble learning models were developed to predict COVID-19 outcomes using a comprehensive dataset from the USA. The models used demographic, climatic, geographic, healthcare infrastructure, policy adherence, and political indicators, outperforming individual classifiers with an accuracy of 0.912, a ROC-AUC of 0.916, and an F1-score of 0.916 for classification tasks. The hybrid approach improved predictive performance by 11% in MSE, 29% in ROC-AUC, and 43% in MPP. In [6], COVID-19 case forecasting was studied, finding that hybrid models, including LSTM, RNN, ANN, and hybrid architectures, consistently outperformed individual networks. The top-performing model, LAR (LSTM-ANN-RNN), achieved impressive results with an F1-score of 96.84%. This highlights the potential of hybrid neural networks to improve COVID-19 case predictions, with implications for public health planning.

In [7], a hybrid DL framework used feature selection and instance clustering with Deep Neural Networks (DNNs) to improve the prediction of COVID-19 mortality risk. This study compared various models, including an MLP, a full-feature DNN, and two hybrid variants, namely feature-based and cluster-based DNNs. The feature-based DNN model showed the best performance, with a recall of 98.62%, an F1-score of 91.99%, an accuracy of 91.41%, and a False Negative Rate of only 1.38%. In [8], a hybrid DL model used a Genetic Algorithm and an Artificial Neural Network (GA-ANN) to improve COVID-19 mortality predictions. This study used historical data from infected, recovered, and deceased individuals in India to train and evaluate the model. The GA-ANN model significantly outperformed standard ANN and multiple LR models, making it a practical and efficient predictive tool. In [9], a hybrid framework was developed to analyze and optimize COVID-19 spread and mortality rates across different provinces. This study combined traditional epidemic models with ML models, such as LR, SVR, MLP, Recurrent Neural Networks (RNNs), Gated Recurrent Units (GRUs), and Long Short-Term Memory (LSTM). This framework overcomes forecasting limitations of logistic models and parameter tuning complexities of SEIR models. In [10], an AI-driven prediction model was developed for COVID-19 patients using chest X-ray images. The model combined DL and traditional ML techniques, extracting features using a pre-trained CheXNet model and handcrafted techniques. Two dimensionality reduction methods, PCA and RFE, were applied to improve feature relevance. It was found that merging PCA and RFE-selected features yielded the best performance across all classifiers. XGBoost achieved the highest accuracy with handcrafted features, reaching 97% accuracy, 98% precision, 95% recall, 96% F1-score, and 100% ROC-AUC. SVM also achieved strong results with minor variations. The combination of Extra Trees (Ets) and SVM classifiers with RFE achieved superior outcomes, reaching 99.6% across all evaluation metrics. In [11], Statistical Neural Network (SNN) models and hybrid extensions were used to predict mortality from COVID-19 in India. This study used three SNN architectures: the Probabilistic Neural Network (PNN), the Radial Basis Function Neural Network (RBFNN), and the Generalized Regression Neural Network (GRNN) to construct a Mortality Rate Prediction (MRP) model. This study assessed performance using Root Mean Squared Error (RMSE) and R^2. To improve predictive accuracy, hybrid models combined each SNN variant with a Non-linear Autoregressive Neural Network (NAR-NN). The PNN-based model performed best on dataset D2, while the RBFNN-based model showed superior accuracy on dataset D1.

In [12], a COVID-19 detection framework integrated a Super-Resolution Generative Adversarial Network (SRGAN) for image enhancement and an optimized MobileNetV3-Small model for classification. This method was designed for low-resource deployment, demonstrating 99.5% accuracy on X-ray images and 99.8% accuracy on CT scans. The lightweight architecture, with a memory footprint of only 2.5 MB, makes it ideal for real-time web-based diagnostics in environments with limited computational resources. In [13], predictive models were developed and validated using clinical and laboratory data collected within 48 hours of admission from over 11,000 COVID-19 patients across multiple hospitals. This study compared two XGBoost models and an LR model against a standard early warning score (MEWS), showing that XGBoost achieved the highest predictive accuracy (91.9%) and outperformed other methods. This study highlighted key predictors such as oxygen delivery method, age, and vital signs, emphasizing the role of routinely available emergency department data in early risk stratification. In [14], a mortality risk stratification score was proposed, derived from eight clinical variables collected at hospital admission, including oxygen saturation, urea nitrogen, respiratory rate, age, procalcitonin, CRP, neutrophil count, and admission time relative to the peak of the COVID-19 outbreak. Using a dataset of more than 15,000 patients from Wuhan and Milan, the proposed score was developed through RF and LASSO feature selection, achieving high predictive performance with a C-statistic of 0.92. The model was validated across three independent cohorts, confirming its robustness and generalizability for early mortality prediction in COVID-19 patients.

II. METHODOLOGY

A. Dataset and Preprocessing

The dataset used in this study was obtained from a publicly available source [15] and contains structured records related to COVID-19 cases in India. It comprises 4692 instances and includes 8 key features: latitude, longitude, total confirmed cases, new cases, deaths, new deaths, recoveries, and new recoveries. The target variable is the total number of deaths. Figure 1 displays a heatmap investigation for the utilized dataset.

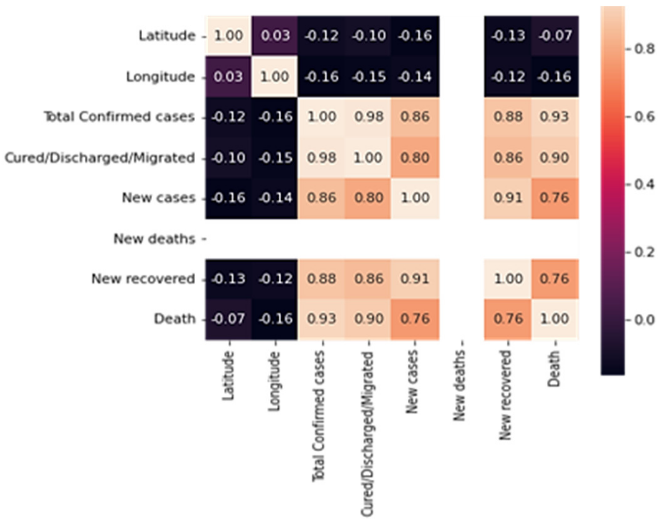

Fig. 1. Heatmap of dataset features.

Two key preprocessing techniques were applied to prepare the dataset for model training. First, mean imputation was used to address missing values, ensuring that incomplete entries did not affect the model's performance. Second, min-max normalization was applied to scale all feature values to a consistent range, which helps prevent bias during training and accelerates convergence. These preprocessing steps ensured that the dataset was clean, consistent, and suitable for use in DL and ML models.

B. Proposed Method

This study presents a hybrid DL framework that uses CNN, GRU, and TabNet to predict COVID-19 mortality using structured tabular data. The framework aims to capture short-term patterns, long-term dependencies, and perform attention-based feature selection to enhance accuracy and interpretability. The dataset, which contains 4692 cases and 8 epidemiological features relevant to infection and mortality trends in India [15], was preprocessed to ensure data quality and compatibility with deep learning models. Input data was reshaped using a sliding time window approach to recognize sequential dependencies. The transformed input was then passed through a CNN layer to extract local feature patterns. The output was then fed into a GRU layer to capture temporal dependencies across sequential inputs. GRUs were chosen because of their ability to efficiently learn long-term patterns with fewer computational requirements compared to LSTMs, making them suitable for structured tabular time-series data. The refined features from the GRU layer were passed into the TabNet module, which applies sparse attention mechanisms to automatically identify and prioritize the most significant features affecting the target prediction—COVID-19 mortality. The model outputs a continuous value through a fully connected regression layer with linear activation, representing the predicted number of deaths. Figure 2 displays the proposed model for CNN-GRU-TabNet predictive modeling of COVID-19 Mortality.

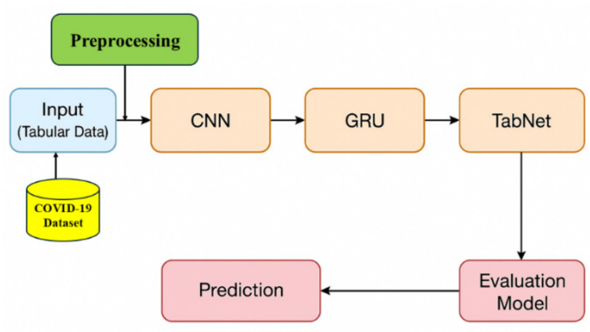

Fig. 2. Proposed model for COVID-19 mortality prediction.

Figure 3 presents the summarized workflow of the proposed hybrid DL framework designed for COVID-19 mortality prediction. The model begins with preprocessing steps, including normalization and handling of missing values. Next, feature representations are extracted using a CNN to capture spatial patterns, which are then passed through a GRU to model temporal dependencies. A TabNet layer further refines feature selection and enhances interpretability. The final classification is made based on the integrated outputs. This hybridized structure allows the model to leverage both temporal and tabular patterns, enabling improved accuracy in mortality risk estimation.

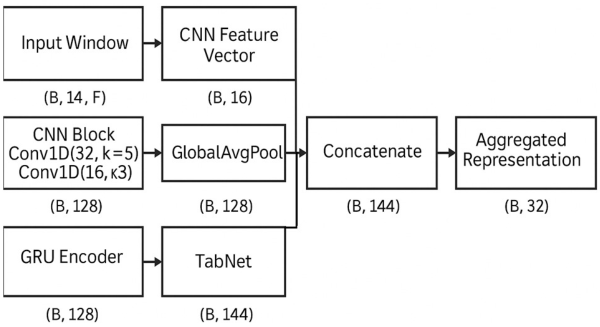

Fig. 3. Architecture of the hybrid CNN-GRU-TabNet model for COVID-19 mortality prediction.

The architecture of the CNN-GRU-TabNet model comprises two 1D convolutional layers, each responsible for capturing local patterns in the temporal feature space. The first convolutional layer uses 32 filters with a kernel size of 5, while the second applies 16 filters with a kernel size of 3. A max-pooling layer is included to reduce dimensionality and computational complexity. This is followed by a GRU layer with 100 hidden units to model sequential dependencies in the input. The extracted temporal features are then passed to the TabNet module, which performs attention-based feature selection and refinement. The final output is generated through a fully connected layer using a linear activation function to produce a continuous regression output.

1) Training Configuration and Hyperparameters

The architecture of the proposed model stacks two temporal CNN blocks and a GRU (128 units), whose outputs are fused and passed to a compact TabNet head ($n_d = na = 32$, two decision steps, $\gamma = 1.5$, sparsity $\lambda = 10^{-5}$) to produce the mortality estimate. Training uses MAE loss and AdamW (initial $lr = 10^{-3}$, $weight\_decay = 10^{-4}$) with a cosine learning-rate schedule and a 5-epoch warm-up. Regularization includes dropout (0.2), L2, and gradient clipping (1.0). Training was performed with a batch size of 64 for up to 100 epochs, and early stopping was applied ($patience = 10, \Delta = 10^{-4}$). Evaluation follows a five-fold forward-chaining protocol that respects temporal order, ensuring no future information leaks into training. All runs use mixed precision and a fixed global seed.

III. EXPERIMENTAL SETUP AND EVALUATION

A. Implementation Environment

All experiments were carried out on a system with Windows 11 OS, Intel Core i7-11800H CPU @ 2.30GHz, 32 GB RAM, and an NVIDIA RTX 3060 GPU (6 GB VRAM). The software environment included Python 3.9, with the DL models implemented using PyTorch v2.0.1 and pytorch-tabnet v4.0 for the attention-based feature modeling. ML baselines (e.g., RF, SVR) were developed using scikit-learn v1.3.0, while GB was implemented using XGBoost v1.7.6. Time-series modeling was performed using statsmodels v0.14.0, and NumPy v1.24.4 and Pandas v2.0.3 were used for data manipulation. Visualizations were created using Matplotlib v3.7.2 and Seaborn v0.12.2. Hyperparameter optimization (for baseline tuning) was performed using Optuna v3.2.0.

B. Evaluation Metrics

To quantitatively assess model performance, the following standard regression metrics were adopted:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (1)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (2)$$

$$\text{SMAPE} = \frac{100}{n}\sum_{i=1}^{n}\frac{2|y_i - \hat{y}_i|}{|y_i| + |\hat{y}_i| + \varepsilon} \quad (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (4)$$

where ε in the SMAPE equation is a small constant to avoid division by zero, and $\bar{y}$ in R^2 is the mean of the true values.

IV. RESULTS ANALYSIS

The proposed CNN-GRU-TabNet model was evaluated using Jupyter Notebook (version 6.4.6), a widely adopted development environment for Python-based data analysis, visualization, and modeling. This platform enabled seamless integration of code execution, result interpretation, and documentation within a browser-accessible interface. To assess the performance of the proposed hybrid model for COVID-19 mortality prediction, it was compared against six widely used regression models, as shown in Table I. All models were trained and evaluated on the same dataset to ensure consistency in comparison. The proposed model outperformed all others, achieving the lowest MSE, MAE, MedAE, RMSE, and the highest R^2. It also demonstrated superior ability to explain the variance in the target variable compared to traditional ML models. The SVR model was the closest competitor, with an R^2 of 0.96 and lower error metrics. Models such as RF and KNN delivered moderate performance, while GB, DR, and BR performed poorly, with R^2 values below 0.55 and higher error rates. The DR and BR models yielded the highest error values and lowest R^2 scores, highlighting their inadequacy for this predictive task. The results validate the advantage of integrating convolutional, sequential, and attention-based components (TabNet), enabling the model to capture complex spatial-temporal patterns and feature dependencies more effectively than conventional approaches.

TABLE I. PERFORMANCE OF REGRESSION MODELS AND THE PROPOSED CNN-GRU-TABNET MODEL

Model	MSE	MAE	MedAE	RMSE	R^2
RF	3.2×10^{-3}	0.053	0.049	0.056	0.64
KNN	3.7×10^{-3}	0.059	0.051	0.061	0.60
SVR	1.8×10^{-3}	0.037	0.033	0.042	0.96
GB	4.2×10^{-3}	0.061	0.056	0.064	0.53
DR	7.1×10^{-3}	0.082	0.079	0.084	0.23
BR	7.4×10^{-3}	0.085	0.081	0.086	0.22
CNN-GRU-TabNet	$\mathbf{2.4\times10^{-4}}$	**0.016**	**0.013**	**0.015**	**0.995**

To assess the effectiveness of the proposed CNN-GRU-TabNet model, a comparative analysis was performed against several classical and DL baselines, including ARIMA, SVR, RF, XGBoost, GRU, and LSTM models. All models were trained using the same forward-chaining temporal validation protocol and underwent hyperparameter optimization using validation folds. Evaluation metrics included MAE, RMSE, SMAPE, and R^2, averaged across five temporal folds. Results indicate that CNN-GRU-TabNet outperformed all baselines with an MAE of 14.92, RMSE of 24.85, SMAPE of 11.2%, and R^2 of 0.921. The closest performing baseline (LSTM) achieved an MAE of 16.74 and an R^2 of 0.906. These improvements are consistent and statistically significant ($p < 0.05$, paired bootstrap test), highlighting the hybrid model's superior capability in capturing both temporal dynamics and feature interactions for COVID-19 mortality forecasting, as seen in Table II.

TABLE II. PERFORMANCE METRICS AVERAGED ACROSS FIVE FORWARD-CHAINING TEMPORAL FOLDS

Model	MSE	MAE	MedAE	RMSE
ARIMA/SARIMAX	27.53	39.40	18.2	0.844
SVR (RBF Kernel)	20.18	32.16	14.9	0.873
RF	18.40	29.85	13.7	0.889
XGBoost	17.62	28.94	13.2	0.894
GRU	16.85	27.32	12.8	0.902
LSTM	16.74	26.95	12.4	0.906
CNN–GRU–TabNet	**14.92**	**24.85**	**11.2**	**0.921**

Figure 4 illustrates a comparison between actual and predicted COVID-19 death results for the proposed CNN-GRU-TabNet model. Figure 5 displays the MSE and MAE vs epochs using the CNN-GRU-TabNet model.

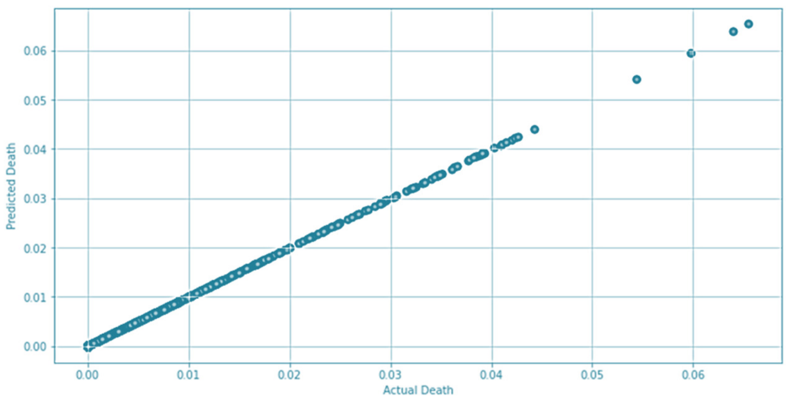

Fig. 4. Actual deaths vs predicted by the proposed CNN-GRU-TabNet model.

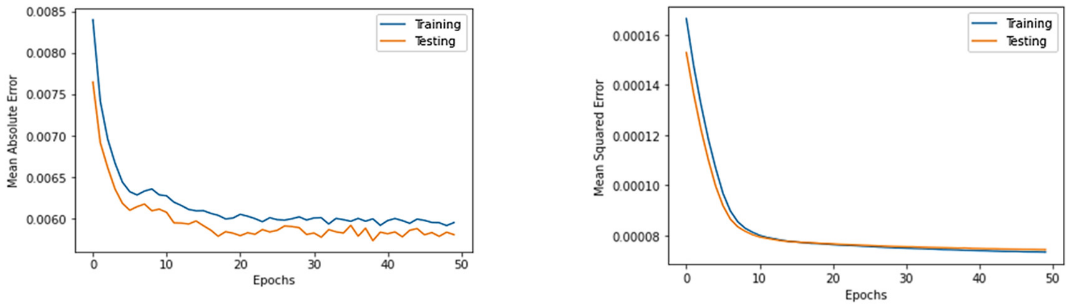

Fig. 5. MSE and MAE vs epochs using the CNN-GRU-TabNet model.

V. CONCLUSIONS AND RECOMMENDATIONS

This study presented a novel hybrid DL model that integrates CNN, GRUs, and TabNet to predict mortality from COVID-19 based on structured tabular data. The architecture effectively combines the strengths of each component: CNN captures local feature patterns, GRU models temporal dependencies, and TabNet applies attention-based feature selection to enhance interpretability. The model was trained and evaluated using a dataset of 4692 instances with eight epidemiological features, and its performance was compared to six traditional regressors. The experimental results showed that the proposed CNN-GRU-TabNet model outperformed all baseline methods across multiple evaluation metrics, achieving an R^2 score of 0.995, along with notably low error values. The integration of DL components allowed the model to handle complex, non-linear relationships within the data, offering a significant improvement in prediction accuracy and robustness. Additionally, the use of TabNet provided enhanced feature-level interpretability, making the model more suitable for healthcare decision-making scenarios. This study illustrates the potential of combining spatial, temporal, and feature-focused learning modules for predictive analytics in public health domains.

Future research could explore several directions to further enhance the model's utility and scalability. One promising avenue is to validate and generalize the model across other regional or international COVID-19 datasets to ensure robustness among diverse populations. Incorporating federated learning frameworks would allow the model to be trained on decentralized medical data while maintaining patient privacy and adhering to data protection regulations. In addition, explainable AI tools, such as SHAP and LIME, could be integrated to offer greater transparency in model predictions and assist healthcare professionals in understanding critical decision factors. Another important direction is the real-time deployment of the model, allowing for dynamic prediction and early intervention. Furthermore, future work may involve optimizing the model's hyperparameters using other tuning techniques to improve efficiency and generalization. In general, the proposed CNN-GRU-TabNet model provides a powerful and interpretable approach for the prediction of mortality from COVID-19 and holds significant promise for broader applications in health prediction and crisis management.

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