Title: Explainable Deep Learning Models for COVID-19 Case Forecasting Using SHAP and LIME

Abstract

Accurate forecasting of COVID-19 case trends is essential for resource planning and public-health decision making. This study explores a suite of deep learning architectures—including LSTM, BiLSTM, RNN, CNN, and multiple hybrid CNN–RNN combinations—for predicting daily COVID-19 case counts. A real-world dataset was preprocessed, normalized, and structured using sliding windows to enable sequential learning. To address the black-box nature of deep neural networks, the system integrates **SHAP** and **LIME**, providing global and instance-level interpretability. Among all models, the **CNN–LSTM hybrid** achieved the best performance, demonstrating superior ability to capture both local temporal patterns and long-range dependencies. SHAP identified recent case spikes and short-term temporal windows as dominant features, while LIME highlighted time-step contributions for individual predictions. The results show that deep learning combined with XAI can deliver both accurate and transparent epidemiological forecasting.

Objective

The primary objective is to build an interpretable COVID-19 forecasting system that integrates deep learning with Explainable AI techniques. The study aims to:

- Compare multiple sequential, convolutional, and hybrid deep learning models
- Evaluate forecasting performance across architectures
- Use **SHAP** and **LIME** to explain feature contributions
- Provide transparent predictions suitable for real-world public-health use
- Identify which temporal patterns most strongly influence future case trends

Method

Dataset

- Real-world COVID-19 daily case dataset
- Time series cleaned, normalized, and converted into supervised sliding-window sequences

Preprocessing

- MinMax scaling for stable neural-network training
- 7–14 day sliding windows
- Train-test split using chronological ordering

Models Implemented

- **Recurrent Models:** LSTM, BiLSTM, RNN
- **Convolutional Model:** 1D-CNN
- **Hybrid Architectures:**
    - CNN → BiLSTM
    - CNN → LSTM
    - MLP → CNN → LSTM
    - CNN → Dense fusion
- **Baseline Model:** MLP

Training

- Optimizer: Adam
- Loss: MSE
- Early stopping to prevent overfitting

Explainability (XAI) Techniques

- **SHAP:** Global and local feature importance
- **LIME:** Instance-level explanations for specific forecast points

Evaluation Metrics

- RMSE
- MAE
- MAPE
- Actual vs Predicted curves
- SHAP summary & dependence plots
- LIME explanation charts

Results Summary

- **CNN–LSTM** achieved the best forecasting accuracy based on RMSE and MAPE.
- SHAP revealed that recent case fluctuations and short-term patterns dominated model decisions.
- LIME demonstrated clear, interpretable time-step contributions for individual forecasts.
- Visual comparison showed that the best model captured rising and falling case trends with minimal prediction lag.

Conclusion

This study demonstrates that combining deep learning with interpretability tools can create accurate and transparent COVID-19 forecasting systems. Hybrid architectures such as **CNN–LSTM** outperform simpler models by capturing both local and long-range temporal dependencies. SHAP and LIME effectively illuminate model reasoning, making the predictions more reliable for public-health decision making. The approach highlights the growing importance of Explainable AI in high-stakes forecasting tasks.