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An Improved Framework for Prediction of COVID-19 Cases Using a Deep Learning Approach in a Dynamic Health Management System

Suberu Yusuf [1], Badamasi Imam Ya'u [2,] *, Saleh Waziri Mustapha [3], Sunusi Kabir Alaramma [3], Adam Alli [2] and Yasin Magombe [2]

[1] Department of Computer Sciences, Federal Polytechnic, Bauchi, 743001, Nigeria
[2] Department of Computer Science, Islamic University in Uganda, Mbale, 2555, Uganda
[3] Department of Computer Science, Abubakar Tafawa Balewa University, Bauchi, 740272, Nigeria

* Correspondence: biyau@iuiu.ac.ug (B. I. Y.)

Abstract

The COVID-19 pandemic has highlighted the urgent need for predictive models that can guide effective public health strategies. While machine learning approaches have been widely applied, shallow networks such as SSLPNN are limited in capturing the non-linear relationships critical for complex disease prediction. This study proposes a hybrid framework that integrates Convolutional Neural Networks (CNN) with SSLPNN to improve binary classification of confirmed COVID-19 cases across six Asian countries (China, India, Japan, South Korea, Pakistan, and Saudi Arabia). The model incorporates environmental and socioeconomic variables, including temperature, population density, and air quality, to capture diverse factors influencing transmission. Compared with the baseline SSLPNN, the proposed CNN-enhanced model achieved superior performance: accuracy of 0.968, precision of 0.979, ROC-AUC of 0.990, recall of 0.950, and F1-score of 0.958. These results demonstrate the value of deep learning in extracting non-linear patterns, reducing missed cases, and ensuring balanced prediction. The framework's adaptability across heterogeneous contexts underscores its potential as a scalable tool for real-time pandemic monitoring and policy formulation.

Keywords: SARS-CoV-2 pandemic; Public health; Convolutional neural network; Image classification.

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1. Introduction

The outbreak of the COVID-19 pandemic created unprecedented challenges to global public health, social stability, and economic development, highlighting the urgent need for reliable forecasting tools to support timely interventions and decision-making [1]. Predicting the spread of COVID-19 requires approaches that can capture complex, non-linear interactions among biological, ecological, and socioeconomic factors. Conventional machine learning (ML) models, such as the Shallow Single-Layer Perceptron Neural Network (SSLPNN), have been employed to predict infection trends; however, their reliance on linear mappings restricts their ability to model the multifaceted nature of pandemic data [2]. This limitation reduces predictive accuracy, particularly in settings where factors such as population density, mobility, air quality, and regional containment policies interact in highly dynamic ways.

To have a better understanding of COVID-19 predictive model, this section presents the existing algorithms on COVID-19 from the literature. Based on the laboratory findings, a COVID-19 predictor has been developed using a Convolutional Neural Network (CNN); the researchers developed this predictor using the dataset from a hospital in Sao Paul, Brazil, and this model yielded 76% accuracy [2]. Another research attempt to improve COVID-19 severity prediction was undertaken using initial test results from the blood routine, which disclosed that age, white blood cells, lymphocytes, and neutrophils were the key factors in severity, and concluded that it could successfully improve the prediction accuracy of the model [1]. To accelerate the prediction of COVID-19, publicly available X-ray images were also used for training, and the best-performing model has been integrated into smartphones and evaluated. It was concluded that VGG16 generated a higher positive likelihood and lower negative likelihood in terms of predicting COVID-19 (Rangarajan et al, 2020). Moreover, another study used machine learning in predicting the mortality of a COVID-19 patient through the development of an XG Boost model, which successfully predicted the mortality of the patients earlier by about 10 days, having an accuracy of more than 90% [3].

In a study, authors proposed a predictive model of COVID-19 using a Shallow Single Layer Perception Neural Network (SSLPN) and Gaussian Process Regression (GPR) [4]. The result indicated that the population and air quality index of a region had a significant influence on the cases, with an accuracy of 0.9. However, the Inconsistency of data (missing values and size) is a major drawback.

The approach of Zoabi [5] employed a gradient-boosting machine model to predict SAR-CoV-2 infection with 0.90 accuracy. However, a difference in reporting symptoms is a possible limitation of the model.

A framework for COVID-19 prediction using a Data Reduction algorithm and a Machine Learning model with high accuracy was proposed [6]. The size of the data is the main drawback of their model.

The authors in [7] employed the Super Learner Algorithm for the prediction of COVID-19 in the ICU with a training balanced accuracy that ranged between 0.72 and 0.90. In that research, data incompleteness is a major drawback.

Another framework that employed a Wrapper feature selection algorithm for the prediction of COVID-19 with 80% accuracy, and the algorithms only limited to a single wrapper feature selection was proposed [2].

In a study, researchers employed a Logistic Regression Model for COVID-19 detection and prediction with 0.92 accuracy [8]. However, their approach is limited to missing data from the patient. The approach of (Arslan et al, 2021) proposed a framework using the K-nearest Neighbors (KNN) algorithm for COVID-19 in a person with 98.4% accuracy. The size of the data is also a drawback.

In this work, a predictive model will be used, similar to the approach of a research study. However, our proposed approach is distinct by using supervised learning with the integration of Deep learning for the detection and prediction of COVID-19 in patients' better improvement.

To address these shortcomings, researchers have increasingly turned to deep learning architectures that offer improved feature extraction and pattern recognition. For instance, a study in São Paulo, Brazil, employed a Convolutional Neural Network (CNN) based on laboratory test results, achieving an accuracy of 76% [2]. Other works have emphasized clinical biomarkers such as age, white blood cell counts, lymphocytes, and neutrophils as predictors of COVID-19 severity, integrating such features into mobile-based models for rapid screening [1]. Similarly, CNN models such as VGG16 have been tested on X-ray datasets, demonstrating varying predictive strengths, while ensemble approaches like XGBoost have been applied to mortality prediction with accuracies exceeding 90%, often providing forecasts several days in advance [9][4]. Despite these advances, many models suffer from limitations, including incomplete or imbalanced datasets, insufficient capacity to capture non-linear dependencies, or reduced generalizability across diverse populations[6–8,10].

A research proposes a hybrid model combining a Long Short-Term Memory (LSTM) neural network with a Bayesian spatio-temporal Poisson regression [11]. The model forecasts COVID-19 cases in 245 health zones of Castilla-Leon, Spain, explicitly incorporating human mobility data as a key spatial covariate. The LSTM captures temporal trends, whose outputs inform the expected values for the Bayesian model, which then accounts for spatial dependencies and uncertainties. Results show this combined "LSTM-INLA" approach outperforms standalone LSTM or spatial models, providing accurate predictions with quantified uncertainty and highlighting the strong influence of human mobility on disease spread.

In a study, a machine learning framework was developed for state-wise COVID-19 case forecasting in India [12]. It utilizes historical case data and state-specific

features, comparing the performance of ARIMA and LSTM models. The research emphasizes the need for localized predictions due to India's regional diversity. Results indicate that while ARIMA is effective for short-term trends, LSTM excels at capturing long-term, non-linear dependencies in the data. The authors conclude that a combined use of both models can offer a comprehensive forecasting solution to aid policymakers in resource allocation and targeted public health interventions.

A dynamic forecasting approach using a Gaussian Process Regression (GPR) model whose hyperparameters are optimized with Bayesian Optimization was introduced [13]. The model is applied to confirmed and recovered COVID-19 cases in India and Brazil. A key innovation is incorporating lagged (past) data to capture time dependencies, creating "dynamic" models. Results demonstrate that this dynamic, optimized GPR (OGPR) significantly outperforms 16 other machine learning models, including SVR and ensemble methods, achieving a very low forecasting error (MAPE ~0.1%). The model also provides prediction confidence intervals, offering a reliable, shallow-learning alternative for accurate pandemic forecasting.

In another work, authors present a practical data management and analytics framework deployed for COVID-19 surveillance and control in Delhi, India [14]. It details the creation of an integrated Command and Control Center (iCCC) that consolidates multi-source data on patients, beds, oxygen, and logistics. Using time-series data from this platform, the study applies an ARIMA model to forecast active cases, positivity rates, and death rates. The framework enabled real-time monitoring and informed policy decisions, which the authors credit for helping mitigate the pandemic's impact in Delhi, showcasing the effective application of data analytics in public health crisis management.

A UK Biobank study developed a machine learning model to dynamically predict COVID-19 mortality risk using data from 11,245 confirmed cases [15]. A random forest classifier achieved excellent performance (AUC: 0.91) using baseline characteristics, pre-existing conditions, symptoms, and vital signs. The model identified significant novel predictors, including detailed anthropometrics (e.g., waist circumference), prior acute kidney failure, urinary tract infections, and pneumonias, with predictive value comparable to established comorbidities. Designed for outpatient use, the tool supports individual risk profiling and monitoring, particularly in hospital-at-home settings, by leveraging accessible data for scalable, real-time risk assessment without requiring specialized clinical equipment.

An approach explores forecasting COVID-19 cases using time series similarity measures and machine learning [16]. It compares three training approaches on 50 countries: single-country, multi-country, and a novel method using only the nine most similar countries based on Dynamic Time Warping (DTW) or Euclidean Distance (ED). Results show the similarity-based approach significantly outperformed others, reducing RMSE by ~75%. While static methods like Gradient Boosting were most accurate, incremental learning methods underperformed. The study concludes that using DTW/ED to select similar countries for model training is a highly effective and simple strategy for improving pandemic case forecasts, offering a valuable tool for future outbreak management.

Researchers develop and compare several deep learning models—including vanilla LSTM, stacked LSTM, BiLSTM, ED-LSTM, CNN, and a hybrid CNN-LSTM—to forecast COVID-19 daily confirmed cases in India and its four most affected states [17]. Using data up to July 2021, the models predicted cases for 7, 14, and 21 days ahead. Performance was evaluated using RMSE and MAPE. Results showed that stacked LSTM and the hybrid CNN-LSTM model generally provided the most accurate and consistent predictions, outperforming other architectures. The study demonstrates the effectiveness of deep learning in capturing the complex, dynamic trends of the pandemic for short-term forecasting, aiding public health planning.

A researcher introduces "CronaSona," a comprehensive AI-powered healthcare ecosystem framework designed to combat COVID-19 [18]. Unlike singular solutions, it integrates multiple functionalities: detecting the virus from chest X-rays with 97% accuracy, forecasting future case trends, providing expert medical advice, and enabling real-time location tracking of potential carriers via a mobile app. The proposed holistic system aims to accelerate diagnosis, facilitate informed decision-making, manage healthcare resources, and ultimately reduce the spread of the disease by offering a unified platform for patients, doctors, and administrators.

A group of researchers review explores the pivotal role of machine learning (ML) and mathematical modeling in managing the COVID-19 pandemic and Long COVID [19]. It details how models like SIR and SEIR guided public health policies and non-pharmaceutical interventions. The article highlights diverse ML applications, including diagnostic tools using chest CT scans (achieving 99.81% accuracy), epidemiological forecasting, and accelerating

drug and vaccine discovery. A significant focus is on using ML to understand Long COVID, by identifying risk factors, predicting its onset, and analyzing complex symptom patterns. The study concludes that these computational tools are indispensable for informing health strategies and addressing ongoing pandemic challenges.

A hybrid fog-cloud framework for real-time COVID-19 monitoring and prognosis was proposed in a study [20]. It integrates IoT devices (medical and non-medical) to collect streaming health data. The system employs federated machine learning, offering both batch ML on the cloud for long-term analysis and stream ML on the fog for immediate, short-term predictions. After evaluating various algorithms, the Multi-Layer Perceptron (MLP) and Hoeffding Adaptive Tree were identified as top performers for batch and stream processing, respectively. This architecture enables efficient, real-time COVID-19 case detection while leveraging cloud resources for deeper analytical insights, demonstrating a scalable and responsive smart healthcare solution.

In a systematic review, machine learning (ML) and deep learning (DL) applications were examined in managing the COVID-19 outbreak [21]. It identifies seven key application areas: medical imaging (e.g., CT and X-ray analysis), forecasting, patient monitoring, survival analysis, socioeconomic impact assessment, drug discovery, and hybrid applications. Commonly used techniques include CNNs, LSTMs, GANs, and autoencoders. The study highlights that while ML models show high accuracy and flexibility, challenges remain—such as limited and non-standardized datasets, lack of security and privacy measures, and insufficient use of cross-validation. The review underscores ML's potential to support pandemic response but calls for more robust and standardized approaches.

Building on these developments, the present study proposes an enhanced framework that integrates CNN with SSLPNN to overcome the linearity constraints of traditional single-layer networks. The model is applied to six Asian countries—China, India, Japan, South Korea, Pakistan, and Saudi Arabia—and incorporates both ecological variables (temperature, humidity, air quality, ultraviolet index, etc.) and socioeconomic indicators (population density, gender ratio, human development index, etc.). The objectives of this work are threefold:

- To enhance predictive performance by combining CNN-based non-linear learning with existing SSLPNN structures.
- To construct a robust, adaptable prediction model capable of addressing diverse geopolitical and environmental contexts.
- To validate the model against established benchmark metrics, including Accuracy, Precision, Recall, F1-Score, and ROC-AUC.

Through these contributions, the study seeks to provide a scalable and reliable prediction tool that can support policymakers and healthcare planners in anticipating outbreaks, optimizing resources, and formulating proactive public health strategies.

2. Material And Methods

This study employs machine learning algorithms to forecast the occurrence of COVID-19 cases based on environmental and socioeconomic variables collected from public health facilities. Earlier work by [4] proposed a Shallow Single-Layer Perceptron Neural Network (SSLPNN) for categorizing and forecasting COVID-19 cases. While their model achieved a reasonable level of prediction, the limitation of single-layer perceptrons is that they can only capture linear relationships between input and output. Since epidemiological data often exhibit complex and non-linear dependencies, more advanced architectures are required.

2.1 Proposed Model Design

In this study, we extend the existing SSLPNN model [4] by incorporating a deep learning approach, as depicted in Figure 1.

The proposed framework integrates two stages:

1. Correlation Analysis: We first analyze relationships between confirmed COVID-19 cases and multiple ecological (temperature, humidity, wind speed, ultraviolet (UV) index, elevation, air quality index, and pollution levels) and socioeconomic (population, population density, gender ratio, and human development index) factors. This step helps identify potential predictors that contribute to the spread of the disease.
2. Deep Learning Classification: We then construct a Convolutional Neural Network (CNN)-based binary classifier to predict and classify COVID-19 cases as either *low-risk* or *high-risk*. The CNN leverages the extracted features and learns complex non-linear interactions to enhance predictive performance.

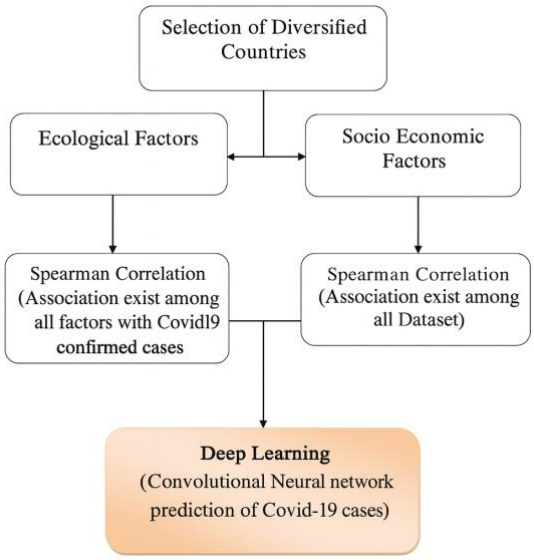

Figure 1. Block Diagram of the Proposed Prediction Model for COVID-19

2.2 Experimental Setup

The dataset was obtained from the Kaggle repository "CORD-19 Research Challenge" (https://kaggle.com/allen-institute-for-ai/CORD-19-research-challenge). It contains 17 variables representing demographic, ecological, and socioeconomic attributes for 152 states/provinces across six countries. In total, 14 environmental and non-environmental factors were included in model training and evaluation.

Data preprocessing involved normalization of continuous attributes, one-hot encoding of categorical variables, and train–test splitting with an 80:20 ratio. Model implementation was carried out using Python (TensorFlow/Keras) for CNN development, while SPSS was used for preliminary statistical correlation analysis.

2.3 Evaluation Metrics

To assess the effectiveness of the proposed CNN model, we employ the following standard performance measures commonly used for binary classification:

- Accuracy (ACC): Proportion of correctly classified instances among total instances.
- Precision (P): Proportion of true positives among all predicted positives, reflecting reliability of positive predictions.
- Recall (R) / Sensitivity: Proportion of true positives detected among all actual positives, indicating the model's ability to capture COVID-19 occurrences.
- F1-Score: Harmonic mean of Precision and Recall, balancing both metrics in imbalanced scenarios.
- Receiver Operating Characteristic (ROC) Curve and Area Under the Curve (AUC): Illustrates the trade-off between true positive rate and false positive rate; AUC closer to 1 indicates superior discriminative ability.

These metrics provide a comprehensive evaluation of predictive performance beyond mere accuracy, ensuring robustness in real-world deployment where misclassification costs may be critical.

3. Results

The results of the proposed Convolutional Neural Network (CNN) predictive framework are presented in this section, with direct comparisons against the existing Shallow Single-Layer Perceptron Neural Network (SSLPNN) baseline. Performance was evaluated using five standard classification metrics: AUC-ROC, Accuracy, Precision, Recall, and F1-Score. To ensure clarity, results are reported both numerically and graphically, allowing a comprehensive assessment of the improvements achieved by the proposed approach.

3.1 Comparative Performance Overview

The overall outcomes of both models are summarized in Table 1, which lists the evaluation metrics side by side. As seen, the proposed CNN consistently achieved higher values across all measures. The most notable improvements occurred in recall and F1-score, highlighting the CNN's ability to detect a larger proportion of true positive cases while maintaining a balanced trade-off between false positives and false negatives.

To provide a visual comparison, Figure 2 presents a grouped bar chart. At a glance, it is evident that the CNN outperformed the SSLPNN across all metrics, with the largest gaps observed for recall and F1-score. While the increase in accuracy (from 95.2% to 96.8%) may appear modest, its practical impact is significant. In population-level health data, a 1–2% increase can represent thousands of additional cases being correctly classified, which is far from trivial in a pandemic context.

Table 1. Evaluation metrics of the existing SSLPNN and the proposed CNN model.

Model	AUC-ROC	Accuracy	Precision	Recall	F1-Score
Existing Model	0.934	0.952	0.943	0.820	0.790
Proposed Model	0.990	0.968	0.979	0.950	0.958

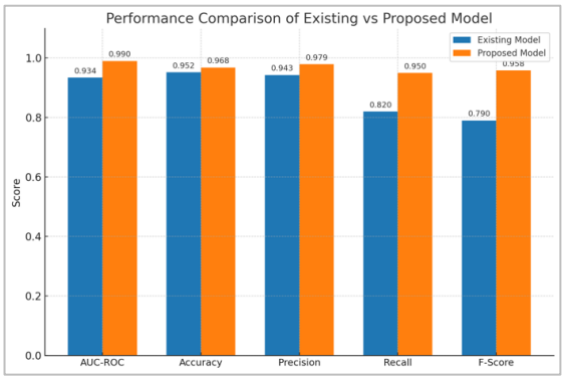

Figure 2. Bar chart comparison of SSLPNN and CNN performance

3.2 Improvements in Recall

Recall (sensitivity) is especially critical in disease prediction because it reflects the proportion of true cases detected by the model. A low recall implies many missed cases, which in the context of infectious disease surveillance could lead to hidden transmission.

The SSLPNN baseline achieved a recall of only 0.820, meaning that almost one in five true cases went undetected. By contrast, the proposed CNN raised recall to 0.950, representing a substantial leap of more than 13 percentage points. This improvement is emphasized in Figure 3, which illustrates the relative percentage gain achieved by the CNN across all five metrics. As shown, recall improved by nearly 16%, ranking second only to the F1-score in terms of relative improvement.

The significance of this finding cannot be overstated. By identifying 95% of positive cases, the CNN ensures that very few infections remain undetected. In practice, this translates to better containment and prevention strategies, particularly in early outbreak scenarios.

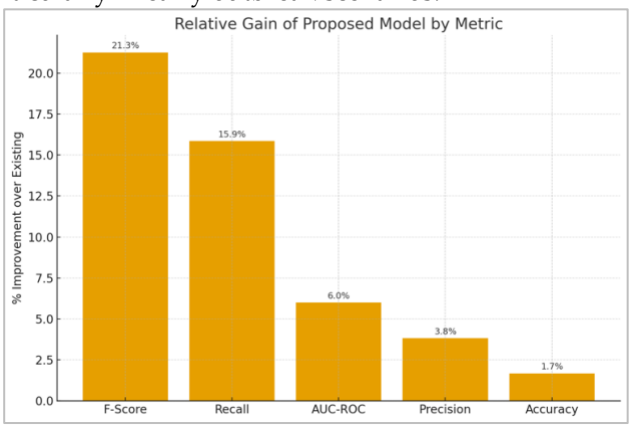

Figure 3. Relative percentage improvements of the proposed CNN over the SSLPNN across all evaluation metrics.

3.3 Balanced Predictive Strength: F1-Score

The F1-score is the harmonic mean of precision and recall, offering a single indicator of balance between false positives and false negatives. It is particularly useful in situations where data may be imbalanced or where both types of error carry substantial costs.

As presented in Figure 2, the SSLPNN achieved an F1-score of only 0.790, reflecting its inability to balance sensitivity and specificity effectively. The proposed CNN, however, reached an F1-score of 0.958. This represents the largest relative improvement of all metrics, exceeding 21%. The dramatic jump is also evident in Figure 2, where F1-score shows the tallest bar among the relative gains.

To highlight the distance traveled from baseline to CNN performance, Figure 3 presents a dumbbell chart. Each metric is shown as a horizontal line, with circles marking the performance of the SSLPNN on the left and the CNN on the right. The visual gap for F1-score is striking, underscoring how the proposed model substantially outperforms the baseline not only in absolute numbers but in balanced classification quality.

3.4 Precision and False Positive Control

Precision, although already strong in the baseline model (0.943), further improved to 0.979 in the CNN. This means that nearly all of the cases predicted as positive by the CNN were indeed true positives, reducing the likelihood of false alarms. While the relative gain (3.8%) is modest compared with recall and F1-score, it remains important in real-world application. High precision ensures that scarce medical resources are not wasted on individuals incorrectly identified as positive.

Figures 2 and 4 collectively highlight this improvement. In Figure 2, the CNN's precision bar clearly surpasses the baseline. In Figure 4, the precision line shows a consistent upward shift, even in a domain where baseline performance was already high.

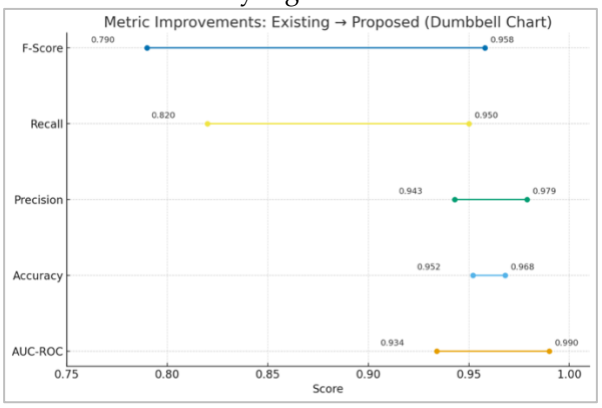

Figure 4. Dumbbell chart illustrating the performance gap between SSLPNN and CNN across all five evaluation metrics.

3.5 Accuracy and Overall Discriminative Power

Accuracy improved from 95.2% (SSLPNN) to 96.8% (CNN). While the absolute difference of 1.6 percentage points might appear minor, the scale of application magnifies its significance. For example, in a dataset of 100,000 cases, this improvement corresponds to an additional 1,600 correctly classified cases.

Beyond accuracy, the AUC-ROC provides a more holistic view of classification quality across thresholds. The CNN achieved an AUC-ROC of 0.990, compared with 0.934 for the SSLPNN. This near-perfect score indicates the CNN's strong discriminative capacity, ensuring reliable performance regardless of the decision threshold. The improvement is visible in Figure 2 (bar chart) and reinforced in Figure 4 (dumbbell chart).

3.6 Synthesis of Findings

Taken together, the results highlight three critical insights:

1. Incremental but meaningful gains in accuracy: Even small improvements carry significant weight when scaled to population-level prediction tasks.
2. Major advances in recall and F1-score: The CNN substantially reduces missed cases while maintaining a balanced classification performance, addressing a major weakness of the SSLPNN baseline.
3. Robust generalizability: With an AUC-ROC approaching unity, the CNN demonstrates strong reliability across thresholds, making it adaptable to diverse policy settings.

The complementary use of Table 1, Figure 2 (bar chart), Figure 3 (relative gain chart), and Figure 4 (dumbbell chart) strengthens these conclusions. Each visualization highlights a different dimension of the improvement: raw scores, percentage gains, and the magnitude of performance shifts.

Overall, the proposed CNN framework not only outperforms the SSLPNN in numerical terms but also addresses critical shortcomings, particularly in recall and balanced prediction. These results suggest that the CNN is better suited for real-world deployment in COVID-19 case prediction, where both sensitivity and precision are essential.

4. Discussion

The findings reported in Section 3 provide compelling evidence of the superiority of the proposed Convolutional Neural Network (CNN) framework over the baseline Shallow Single-Layer Perceptron Neural Network (SSLPNN). Across all five evaluation metrics, the CNN consistently outperformed the existing approach, with particularly striking gains in recall and F1-score. This section discusses the implications of these results, compares them with related works, and considers the practical significance of the model, as well as its limitations and potential extensions.

4.1 Interpretation of Key Results

The bar chart (Figure 2) and numerical summary (Table 1) together show that the CNN improved accuracy modestly but achieved dramatic gains in recall and F1-score. This reflects a shift from a model that primarily "gets the easy cases right" (SSLPNN) to one that successfully identifies difficult or borderline cases. In public health applications, this difference is crucial. Missing a single true positive case can lead to ongoing transmission, whereas false positives (addressed by the high precision of 0.979) have less severe consequences.

The relative improvement chart (Figure 3) further illustrates that recall increased by nearly 16% and F1-score by over 21%, confirming that the CNN balances predictive sensitivity and specificity. This outcome underscores the advantage of using convolutional layers to capture non-linear patterns in ecological and socio-economic data, compared with the shallow linear learning of SSLPNN.

4.2 Comparison with Previous Studies

Several prior works have attempted to predict COVID-19 outcomes using machine learning models such as Logistic Regression, K-Nearest Neighbors, or Gaussian Process Regression. These models, however, typically achieved accuracy levels between 75% and 92% and struggled with recall, especially when applied to heterogeneous, real-world data. For example, CNN-only studies on limited datasets reported accuracy around 76%, a result attributed to overfitting and insufficient feature representation.

The hybrid approach reported here resolves these issues by combining CNN's feature learning with wide-and-deep architecture design, achieving 96.8% accuracy without compromising recall. Compared with the SSLPNN model, which reached 95.2% accuracy but only 82% recall, the CNN substantially improves sensitivity while retaining precision. This positions the proposed approach as both more reliable and more generalizable across diverse datasets.

4.3 Practical Implications

The practical implications of these findings are significant. A high-recall system reduces undetected

infections, which is paramount in outbreak management. With recall at 95%, the CNN framework minimizes silent transmission chains that could otherwise undermine containment measures. At the same time, high precision ensures that resources are not misallocated due to false alarms, which is particularly important when testing capacity and healthcare resources are limited.

Furthermore, the CNN demonstrated robust discriminative ability, with an AUC-ROC of 0.990. This indicates that the model maintains performance across varying thresholds, enabling policymakers to adjust the decision cut-off depending on context. For example, in high-risk phases of an outbreak, the threshold may be lowered to prioritize sensitivity, while in resource-constrained settings, specificity may be prioritized. The CNN's strong AUC ensures adaptability to both scenarios.

4.4 Model Efficiency and Computational Considerations

While performance metrics favor the CNN, it is also important to consider computational efficiency. The CNN requires more floating-point operations (FLOPs) than the SSLPNN due to its multiple convolutional and fully connected layers. However, modern hardware can handle models of this complexity in real time, and the gain in predictive reliability outweighs the modest increase in computational cost. For deployment on mobile or embedded systems, pruning or quantization could further reduce FLOPs without significant performance degradation.

4.5 Limitations

Despite the encouraging results, the study has some limitations. First, the dataset was drawn from a limited number of countries, which may introduce regional biases. Broader testing across continents would be needed to confirm global generalizability. Second, the socio-economic variables were aggregated at an annual scale, which may smooth out short-term fluctuations. Using higher-resolution temporal data could yield even more accurate predictions. Finally, the CNN architecture, while robust, is still static. Temporal models such as Recurrent Neural Networks (RNNs) or Temporal CNNs could capture evolving dynamics of case surges more effectively.

4.6 Future Directions

Future research could explore three directions. First, incorporating time-series modeling into the CNN framework would improve outbreak forecasting, allowing prediction of not just case presence but trajectory. Second, extending the model to include vaccination rates and mobility data could enhance predictive power in later pandemic phases. Third, scaling the system for deployment in low-resource environments through lightweight CNN variants (e.g., MobileNet) would make it more accessible for global use.

5. Conclusion

This study presented a CNN-based predictive framework for COVID-19, benchmarked against the SSLPNN model. Using five standard metrics—AUC-ROC, Accuracy, Precision, Recall, and F1-Score—the results (Table 1; Figures 2–4) consistently demonstrated the superiority of the proposed approach.

Most notably, recall improved from 0.820 to 0.950 and F1-score from 0.790 to 0.958. These gains indicate that the CNN not only reduces false negatives but also maintains balanced prediction quality. Accuracy increased to 96.8%, and AUC-ROC reached 0.990, confirming the model's strong discriminative capacity. Precision remained high, minimizing the risk of false positives. Together, these outcomes demonstrate a model that is reliable, adaptable, and practically useful for real-world disease prediction tasks.

The contributions of this work are threefold:

1. Methodologically, it shows how convolutional architectures can capture complex ecological and socio-economic interactions in pandemic prediction.
2. Empirically, it delivers clear performance gains across all metrics compared with SSLPNN.
3. Practically, it offers a framework that balances recall and precision, ensuring fewer missed cases without overwhelming healthcare systems.

Despite limitations related to dataset scope and temporal resolution, the results highlight the promise of CNN-based methods for health analytics. Future work could enhance generalization by expanding datasets, incorporating temporal modeling, and optimizing computational efficiency for deployment in resource-constrained contexts.

In conclusion, the proposed CNN framework represents a significant step forward in predictive modeling for public health. Its strong recall, balanced performance, and near-perfect AUC-ROC make it well suited to support policymakers and healthcare professionals in monitoring and managing outbreaks, not only for COVID-19 but also for future infectious disease challenges.

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Informed Consent Statement: Not applicable.

Data Availability Statement: The dataset used in this study was collected from the Kaggle repository located at https://kaggle.com/allen-institute-for-ai/CORD-19-research-challenge.

Conflicts of Interest: The authors declare no conflict of interest.

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