

AI-Driven Pandemic Outbreak Prediction using a Hybrid SEIR-LSTM Framework

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Abstract—This research provides an intelligent system that combines epidemiological modeling and machine learning techniques to anticipate pandemic breakouts. While a hybrid mix of the SEIR model and Long Short-Term Memory (LSTM) networks covers the temporal dynamics of disease transmission, the suggested framework uses logistic regression for precise risk classification. In order to produce accurate predictions of possible epidemics, the system analyzes both historical and current health data to find important patterns, trends, and linkages.

The system includes an interactive chatbot in addition to prediction, which is intended to improve accessibility and user engagement. The approach is helpful for analysis and public guidance since the chatbot offers current information, individualized risk evaluations, and valuable safety recommendations. The suggested model is a reliable and useful tool for pandemic prediction and well-informed healthcare decision-making, as evidenced by experimental findings showing an accuracy of roughly 89.6 percent.

Index Terms—Location-Based Risk Assessment, Artificial Intelligence, Machine Learning, Pandemic Prediction, SEIR Model, LSTM, Chatbots, Risk Management, and Vaccination Effectiveness.

I. INTRODUCTION

More efficient early warning systems are desperately needed, as seen by the recent sharp increase in infectious diseases. The COVID-19 pandemic revealed serious flaws in the current healthcare system, impacting not only public health but also the global economy and societal stability. Conventional forecasting methods frequently find it difficult to adjust to quickly changing circumstances and the growing amount of complicated, real-time data because they primarily rely on statistical and epidemiological models. Because of this, early outbreak identification and precise outbreak prediction continue to be difficult challenges.

Promising remedies to these constraints are provided by developments in machine learning (ML) and artificial intelligence (AI). Large-scale healthcare and environmental datasets may be processed thanks to these technologies, which make it possible to find hidden patterns and trends that conventional approaches could miss. While deep learning approaches are very good at identifying temporal dependencies and intricate interactions within sequential data, machine learning methods increase prediction accuracy.

This research suggests an AI-powered approach for predicting pandemic outbreaks. The framework combines several methods to improve forecasting accuracy. The chance of an epidemic is estimated using logistic regression, and the temporal progression of disease propagation is modeled using a hybrid technique that combines the SEIR model and long short-term memory (LSTM) networks. The algorithm can more accurately forecast infection trends and evaluate outbreak risks because of this combination.

The system also includes an interactive chatbot to enhance accessibility and usability. Users can assess their own risk levels, get real-time updates, and obtain practical advice about possible outbreaks thanks to this tool. The suggested method becomes more useful and practical for real-world applications by combining predictive analytics with an intuitive user interface. The system's overall goal is to offer a dependable and scalable instrument that facilitates public health decision-making, improves readiness, and lessens the effects of future pandemics.

II. LITERATURE SURVEY

Extensive research into creating precise and effective prediction systems has been prompted by the rising frequency of infectious disease outbreaks. Artificial intelligence (AI) and

machine learning (ML) are becoming crucial technologies for epidemic forecasting and analysis due to the expansion of healthcare data and computational power. Numerous research studies have shown that by examining intricate and sizable datasets, AI-based methods may greatly increase early detection and prediction accuracy [6], [14].

The capacity of deep learning methods, especially Long Short-Term Memory (LSTM) networks, to model time-dependent data has drawn a lot of interest. These models are useful for forecasting epidemics because they are very good at identifying long-term patterns and trends in infection data. When used in disease transmission analysis, research has demonstrated that LSTM-based models yield more accurate predictions than conventional statistical techniques [1], [9], [22]. Furthermore, by identifying sequential dependencies in data, recurrent neural network-based techniques improve time-series prediction skills even further [15].

Additionally, risk classification and disease prediction have made extensive use of machine learning models. The chance of outbreaks can be estimated and trends in past datasets can be found using methods like logistic regression and other supervised learning algorithms. These techniques are especially helpful for assisting healthcare systems' decision-making processes [2], [20]. Additionally, explainable AI has been developed to enhance these models' interpretability, allowing for greater comprehension and confidence in predicting results [6].

Conventional epidemiological models are still essential for comprehending the spread of disease. A formal framework for illustrating how diseases spread throughout populations is offered by models like the SEIR Model. Nevertheless, these models frequently rely on set parameters and presumptions, which restricts their capacity to adjust to quickly shifting real-world circumstances. In order to get over this restriction, hybrid strategies that combine machine learning methods with epidemiological models have been put forth, which improve prediction accuracy and flexibility [8], [11].

In order to improve forecasting effectiveness, recent developments have also concentrated on combining various data sources. Clinical, environmental, and demographic data can be combined through multi-source data integration, resulting in more thorough analysis and better prediction results [7]. In a similar vein, big data analytics has been applied to process massive amounts of data and derive valuable insights for pandemic forecasting [5], [19].

Disease monitoring systems have been reinforced by the application of Internet of Things (IoT) technology in healthcare. Continuous data collection and real-time monitoring are made possible by IoT-based systems, which can help with early epidemic detection and enhance response plans [3], [17]. Furthermore, federated learning methods have been developed to guarantee data sharing that protects privacy, enabling cooperation between several businesses without disclosing private information [4].

COVID-19 prediction using deep learning and machine learning methods has been the subject of several investigations.

These methods have improved comprehension and management of pandemic scenarios and shown the efficacy of AI in real-time forecasting [2], [10], [16]. In order to improve prediction performance, survey-based research also emphasizes the increasing significance of combining sophisticated computational techniques with conventional models [13].

Despite these developments, there are still issues with current methods, including their limited adaptability, high processing demands, and inability to capture both the structural and temporal aspects of disease propagation. Recent research highlights the usage of hybrid frameworks, which integrate the advantages of several approaches, to address these problems.

Inspired by these advancements, the suggested solution combines deep learning and machine learning techniques to enhance pandemic forecasting. The system seeks to provide precise outbreak prediction and efficient disease progression analysis by fusing risk classification approaches with time-series forecasting models, thereby assisting healthcare systems in making better decisions.

III. METHODOLOGY

The suggested methodology provides precise and organized predictions of pandemic outbreaks by combining machine learning methods with conventional epidemiological models. Fig. 1 depicts the system's total workflow. The framework ensures dependability and adaptability in real-world situations by converting unprocessed data into insightful knowledge through a methodical approach.

The first step in the process is gathering information from many sources, including real-time updates, environmental reports, and medical records. After that, this data is processed and cleansed to eliminate discrepancies and enhance quality. The system finds the most pertinent characteristics that affect the spread of disease after preprocessing. Predictive models that can spot trends and predict future outbreaks are trained using these characteristics. Lastly, the system produces outcomes that help people and healthcare authorities make wise decisions.

A. Data Collection

Getting the pertinent data needed for prediction is the first step. Data on infection rates, recovery counts, vaccination status, population density, and environmental variables like humidity and temperature are gathered from public health statistics and other trustworthy sources.

By gathering information from many sources, the system is able to identify certain factors that affect the transmission of disease. This guarantees that the models are trained on extensive and realistic datasets, enhancing their capacity for prediction.

B. Data Preprocessing

Inconsistencies, duplicate entries, and missing values may be present in the gathered data. In order to clean and arrange the dataset, preprocessing is carried out.

Appropriate techniques, including estimation or elimination, are used to deal with missing values. To ensure data accuracy,

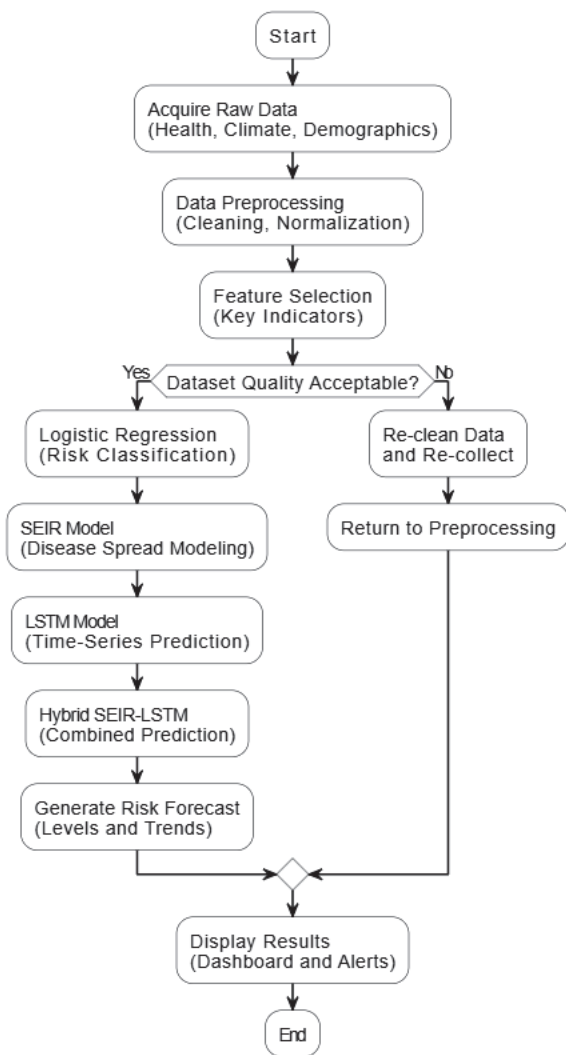


Fig. 1. Workflow of the proposed AI-based pandemic prediction system.

duplicate records are removed. While categorical data is transformed into a format appropriate for machine learning models, numerical data is standardized to guarantee consistency.

By ensuring that the dataset is trustworthy and appropriate for additional research, this step immediately enhances model performance.

C. Feature Selection and Extraction

Not every piece of information gathered can be used to make predictions. At this point, the system chooses the most crucial elements—such as infection trends, recovery rates, and demographic characteristics—that have a major impact on the spread of illness.

To bring all variables into a comparable range, feature scaling is also used. As a result, the models train more efficiently and make more accurate predictions. The system becomes more accurate and efficient by concentrating solely on pertinent features.

D. Logistic Regression for Risk Classification

Regions can be categorized into low, medium, and high risk levels using logistic regression. To calculate the likelihood of an outbreak, the model examines correlations between variables such as recovery patterns, population density, and infection rates.

For categorization jobs, this approach is straightforward, comprehensible, and efficient. It facilitates the prompt identification of high-risk locations, enabling early preventive measures.

E. SEIR Model for Disease Dynamics

The SEIR model is used to comprehend how diseases propagate throughout a community. The population is separated into four groups: recovered, infectious, exposed, and vulnerable.

The approach provides insights into the course of the disease by tracking how people shift between different groups over time. This aids in identifying trends in outbreaks and forecasting their future spread.

F. LSTM for Time-Series Prediction

Time-based data, such as daily infection counts, are analyzed using Long Short-Term Memory (LSTM) networks. Long-term dependencies and trends in sequential data can be captured by LSTM models.

This enables the system to learn from past trends and make more accurate predictions about future infection rates.

G. Hybrid SEIR-LSTM Model

The suggested technique creates a hybrid prediction model by fusing the SEIR model with LSTM networks. While LSTM improves prediction accuracy by learning from actual data, the SEIR model offers a theoretical understanding of illness spread.

By making forecasts more dependable and flexible in response to shifting circumstances, this combination enhances the system's overall performance.

H. Prediction and Output

Lastly, the system makes predictions and displays them in an understandable manner. Outbreak projections, risk assessments for various areas, and visual aids like maps and charts are among the deliverables.

These findings enable people to comprehend their risk levels and assist healthcare authorities in planning interventions. All things considered, the approach facilitates prompt decision-making and lessens the effects of pandemics.

I. System Architecture

The suggested method's system architecture, shown in Figure 2, is intended as a comprehensive pipeline that integrates intelligent modeling techniques with real-world data for pandemic prediction. The method starts with a variety of data sources, including demographic statistics, environmental variables, and medical records, which collectively offer a comprehensive picture of disease-related aspects. In order to

make sure the data is consistent and appropriate for analysis, mistakes are eliminated, missing values are addressed, and normalization is applied during the preprocessing stage.

Following data preparation, the most significant characteristics are chosen and scaled to enhance model performance during the feature engineering phase. Several analytical models are then used to process these features. Initial risk levels are estimated using logistic regression, which provides a straightforward but efficient way to categorize infection risk. While the LSTM model uses time-based patterns to forecast future trends from historical data, the SEIR model simulates how the disease spreads throughout various population groups.

A hybrid SEIR–LSTM prediction engine, which combines deep learning-based forecasting and epidemiological knowledge, combines the outputs from the SEIR and LSTM models to increase accuracy. The results of the logistic regression provide additional support for this hybrid output, strengthening the overall predictions. A backend server then oversees model integration, API communication, and system control for all created outputs. For later usage and analysis, the processed findings are kept in a database. Lastly, a user interface in the form of an interactive dashboard and chatbot is used to provide the insights, making it simpler for users like policymakers and healthcare professionals to comprehend and implement the forecasts.

IV. RESULTS AND DISCUSSIONS

The efficacy of the suggested AI-powered pandemic prediction system in risk classification and time-series forecasting was assessed using historical healthcare records. The accuracy of classifying outbreak risk levels and the precision of forecasting infection patterns over time were the two main focuses of the examination.

Based on epidemiological variables, regions were categorized into three risk levels using the Logistic Regression model: low, medium, and high. Simultaneously, the trajectory of infection cases over time was predicted using the hybrid SEIR–LSTM model. When combined, these models show how the system can facilitate both temporal epidemic prediction and spatial risk assessment.

As seen in Fig. 3, the system also produces a real-time risk visualization map that illustrates the geographic distribution of infection severity throughout India, with a special emphasis on southern areas. Because of their increased case density in relation to population, areas like Raichur and Bidar are designated as high-risk zones. This spatial representation makes it possible to quickly identify areas that are at risk, facilitating prompt intervention and effective resource distribution. The hybrid SEIR–LSTM strategy frequently outperforms separate models, according on a comparison of model performance. Its ability to integrate the sequence-learning capabilities of LSTM networks with the structured epidemiological insights of the SEIR model accounts for this improvement. The hybrid model exhibits more resilience and reliability by closely matching observed data with projected infection trends.

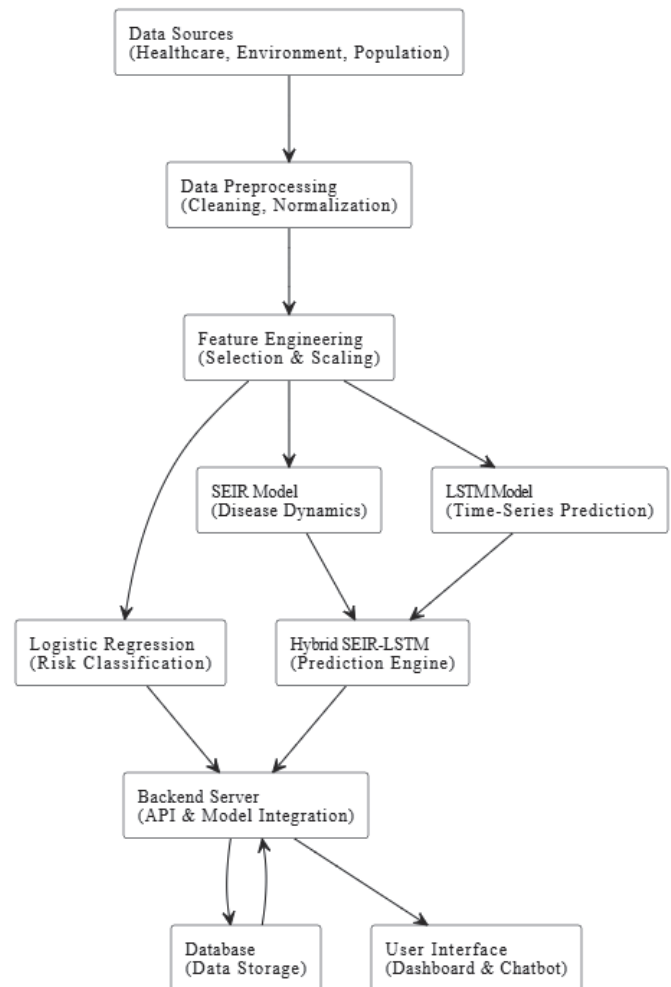


Fig. 2. System architecture of the proposed AI-Powered Pandemic Outbreak Predictor.

A combined view of important public health parameters, such as the overall population, vaccination coverage, confirmed cases, and high-risk areas, is provided by the vaccination analytics dashboard, which is seen in Fig. 4. This makes it possible to track vaccination rates and the intensity of outbreaks in various regions more effectively. Using region-specific stock data, the Vaccine Request Portal (Fig. 5) enables users to request doses and verify vaccine availability. Additionally, the system has an automated notification system that sends users an SMS when vaccines are made available in the area they have chosen. Currently, a number of areas, including Bangalore, Bidar, Hubli, Mysore, and Raichur, show little or no supply, underscoring the necessity of effective distribution plans. Based on updated datasets, the News and Updates module (Fig. 6) offers region-specific health insights and real-time risk analysis. For instance, variables like case count, population density, and insufficient vaccination coverage support Raichur's high-risk designation with high confidence. Using logistic regression, the approach divides areas into low, medium, and high risk groups so that authorities can efficiently

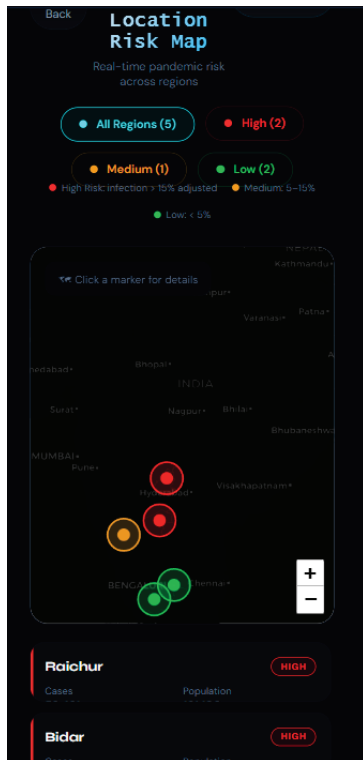


Fig. 3. Location risk map of pandemic spread in India.

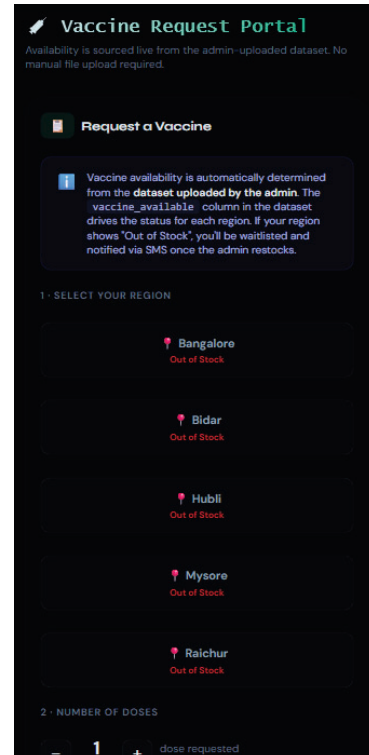


Fig. 5. Vaccine availability and request portal interface.

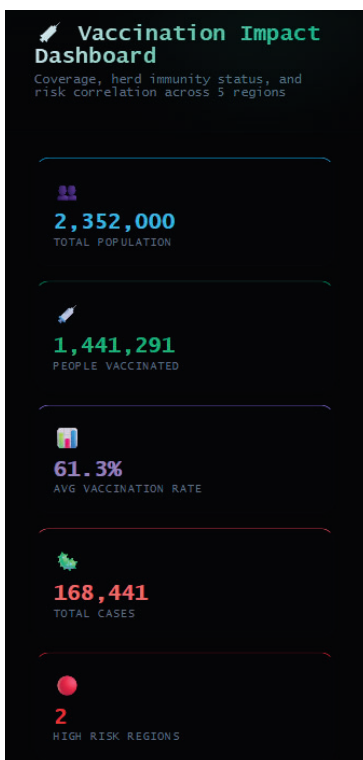


Fig. 4. Vaccination impact analytics dashboard.

prioritize initiatives. Epidemiological datasets in structured forms like CSV can be automatically ingested thanks to the Smart Data Upload module (Fig. 7). The technology reduces human labor and increases productivity by processing the data after it has been uploaded and producing AI-driven analytical reports. Lastly, a comparison of several regions based on infection rates, vaccination coverage, and anticipated risk levels is provided by the AI Risk Dashboard, which is displayed in Fig. 8. Due to low vaccination rates and high case counts, areas like Raichur and Bidar are categorized as high risk, but Hubli is classified as medium risk. To facilitate real-time monitoring and decision-making, the dashboard employs a structured card-based architecture with distinct visual cues.

V. CONCLUSION

This study combined machine learning methods with conventional epidemiological modeling to propose an AI-driven framework for pandemic outbreak prediction. The suggested system successfully captures both disease transmission dynamics and temporal infection patterns by combining a hybrid SEIR-LSTM model with Logistic Regression for risk classification. The system is able to produce accurate and significant epidemic trend predictions by utilizing a variety of data sources, including demographic statistics, environmental factors, and medical records.

The evaluation results show that the hybrid approach outperforms individual models in terms of accuracy, underscoring its capacity to manage the complexity and non-linearity of disease propagation in the real world. Apart from forecasting, the

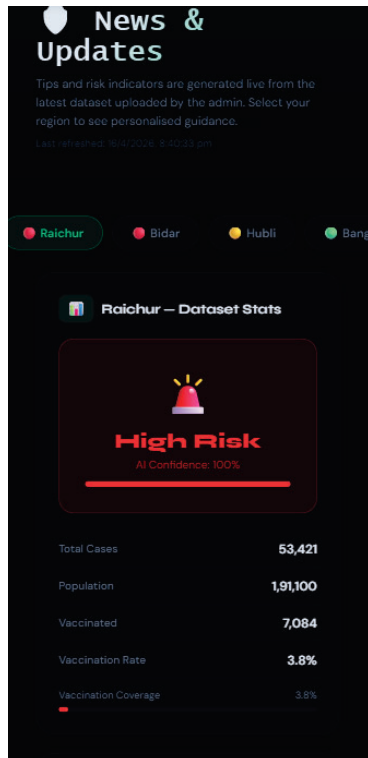


Fig. 6. News and updates module with region-specific risk analysis.

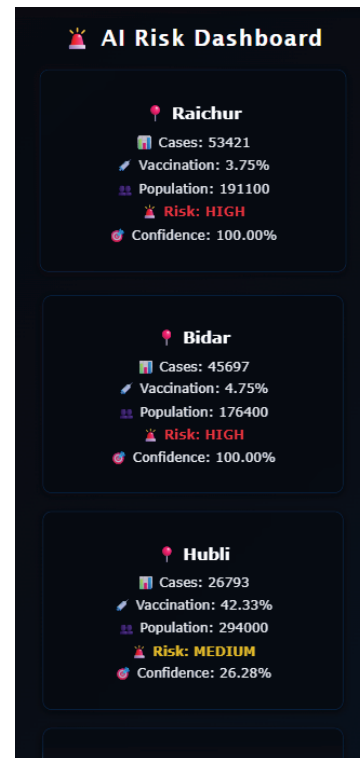


Fig. 8. AI risk dashboard for region-wise epidemiological assessment.

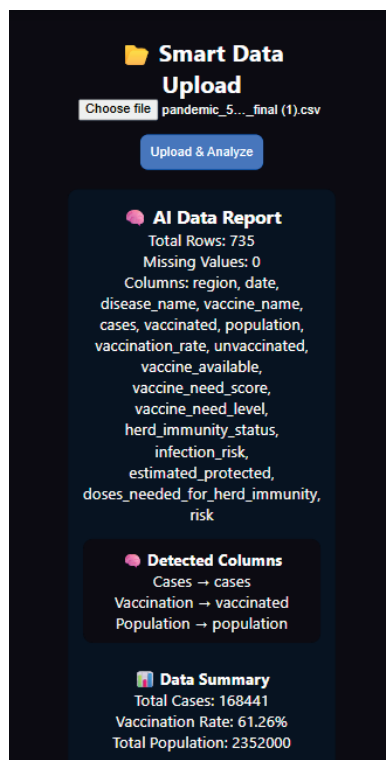


Fig. 7. Smart data upload and AI-based analysis module.

technology improves usability by providing real-time access to risk levels, outbreak forecasts, and region-specific data through an interactive dashboard and chatbot.

All things considered, the suggested system provides a workable and expandable solution that can support early warning systems and help healthcare authorities make prompt and well-informed judgments. The approach helps develop better preparedness and response plans for upcoming pandemics by fusing data-driven intelligence with epidemiological knowledge.

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