Deep learning for infectious disease surveillance integrating internet of things for rapid response

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ABSTRACT

Particularly in the case of emerging infectious diseases and worldwide pandemics, infectious disease monitoring is essential for quick identification and efficient response to epidemics. Improving surveillance systems for quick reaction might be possible with the help of new deep learning and internet of things (IoT) technologies. This paper introduces an infectious disease monitoring architecture based on deep learning coupled with IoT devices to facilitate early diagnosis and proactive intervention measures. This approach uses recurrent neural networks (RNNs) to identify temporal patterns suggestive of infectious disease outbreaks by analyzing sequential data retrieved from IoT devices like smart thermometers and wearable sensors. To identify small changes in health markers and forecast the development of diseases, RNN architectures with long short-term memory (LSTM) networks are used to capture long-range relationships in the data. Spatial analysis permits the integration of geographic data from IoT devices, allowing for the identification of infection hotspots and the tracking of afflicted persons' movements. Quick action steps like focused testing, contact tracing, and medical resource deployment are prompted by abnormalities detected early by real-time monitoring and analysis. Preventing or lessening the severity of infectious disease outbreaks is the goal of the planned monitoring system, which would enhance public health readiness and response capacities.

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1. INTRODUCTION

To address the problem of many coronavirus disease 2019 (COVID-19) patients with paper forms for investigation and medical staff-public health unit communication. We designed and developed an infectious disease monitoring system data translation using the agile methodology to allow a project to react to change requests quickly [1]. These data modifications enable regular, COVID-19, event-based, and epidemic surveillance in public health emergencies. Emerging infectious disease prevention, containment, and prediction are essential for managing their spread and impact [2]. Infectious illness management has used several modeling methods. Emerging illnesses are connected to selected human forces like urbanization and habitat fragmentation. Infectious illness pandemics damage lives and property and provoke fear and unrest. Establishing an infectious disease early warning platform and taking timely actions to avert outbreaks is crucial [3]. It includes infectious disease early warning system terms, national and global development status, indicators of infection and systems, and sources for establishing them. Real-world applications often face similar imputation challenges that are difficult to solve [4]. Kernel-based learning technique uses location-specific disease-related risk factor features from diverse data sources to address this difficult challenge.

Prevention, health, and social good depend on early detection and control of infectious illnesses via active monitoring [5]. Intelligently picking a small group of nodes as sentinels from many persons to identify infectious disease outbreaks early is a tough task in active surveillance [6]. Existing sentinel sampling techniques based on global social network information could be more efficient and precise. Some studies heuristically pick sentinels using local knowledge about linked neighbors. Few consider the time structure of social ties, which may directly affect infectious illness propagation [7]. Based on the friendship paradox hypothesis, which states that most individuals have fewer friends than their friends, we offer two temporal-network surveillance algorithms for choosing sentinels. Infectious monitoring is one of the most complete systems for collecting, analyzing, and interpreting data on infectious disease proliferation, vectors, and outbreaks. Additionally, data should be provided quickly to regulate infectious illness prevention [8]. An infectious illness prediction model is crucial for real-time management. Construct a model utilizing long short-term memory (LSTM) that can forecast the epidemic disease's location and intensity. Infectious disease surveillance is an essential aspect of healthcare, as shown in Figure 1.

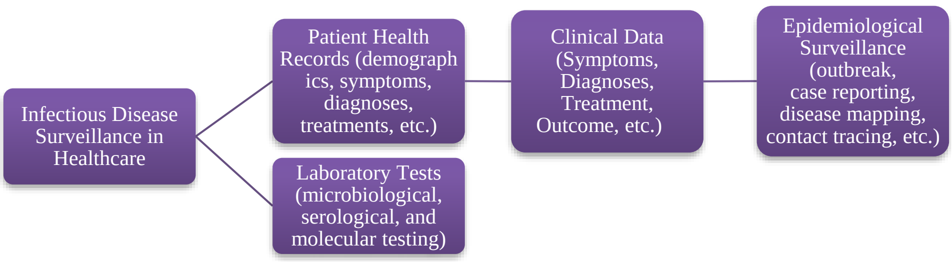

Figure 1. Infectious disease surveillance healthcare essentials

This work provides a crowdsourcing technique for low-cost, real-time community monitoring and mass temperature screening modules based on thermal imaging [9]. This is in response to the current epidemic of infectious illnesses in humans and animals. Therefore, planning and executing thorough actions to avoid diseases, manage them effectively, and forecast when they will spread is critical [10]. Yet, there needs to be an appropriate comparison of time series analytic methods for various illnesses, such as measles, dengue fever, and hand-foot-mouth [11]. Time series analysis will be used in this research to compare the Seasonal ARIMA model with other models for forecasting the hand foot mouth, dengue, and measles.

Infectious illnesses are top global health concerns. Due to human, biological, climatic, and ecological causes, many illnesses emerged. Infectious infections have spread worldwide in the recent decade [12]. This condition emphasizes the necessity for a rapid disease detection system to detect, diagnose, and control pandemic diseases. The Indian surveillance system, particularly Kerala, is reviewed. Existing surveillance systems can detect global or national epidemics [13]. It can notify health professionals with detailed data. Infectious illnesses lead to mortality and economic damage globally. A more resilient, adaptive, and adaptable structure would enhance epidemic response [14]. Engineers build and construct infrastructure so novel infectious disease treatment technologies may be implemented in current structures with efficiency and resources before a public health disaster. Outbreaks may overwhelm frail health systems that need more resources, infrastructure, regulations, and protocols to protect populations. Pakistan needs a centralized health and disease surveillance system. Physical and electronic media report ailments in the present manual disease monitoring system. Due to the delay, epidemics are reported in print and electronic media [15]. The system disease outbreak countermeasures and may induce widespread panic. It provides a cloud-based health management system with trend analysis for illness monitoring and early warning. Public health officers may employ timely and meaningful health data in a surveillance system and a data-driven forecasting model [16]. The disease surveillance system may detect public health hazards and multi-disease outbreaks. The major purpose of this computer approach is to prevent viral transmission and infection. For this, medical routes are prioritized by demographic groupings [17].

Delays in identifying and reacting to outbreaks are common in current infectious disease monitoring systems due to a need for proactive response capabilities and real-time data integration. A system that uses deep learning and internet of things (IoT) technology is needed to identify infectious disease outbreaks quickly, intervene promptly, and allocate resources effectively. This system would help to reduce the impact of pandemics.

This paper proposes using IoT sensors for real-time infectious illness monitoring in conjunction with deep learning methods, namely recurrent neural networks (RNNs). Thanks to this connection, the system can now examine more types of data and spot irregularities that might be signs of disease outbreaks. The proposed method may early predict infectious disease outbreaks by using RNNs to identify small temporal trends in health data gathered from IoT devices. Technology can also predict when illnesses will spread, allowing prompt preventative management. By combining geographical data from IoT devices, the system can perform spatial analysis, pinpoint hotspots, and follow infected people wherever they perform. With this expertise, we can better understand the dynamics of disease spread and respond with precision.

The proposed system enables real-time monitoring of health indices and illness trends via continuous data collecting and analysis. Because of this, public health officials may quickly respond by deploying medical resources to impacted locations, conducting targeted testing, and tracking contacts. The proposed system enhances public health preparation and response capacities, which offers timely and actionable information in the face of infectious disease epidemics. In the end, it helps lessen the effect of pandemics and save lives by allowing preemptive intervention measures, allocating resources, and disseminating timely public health warnings.

Cluster analysis in medicine and monitoring systems led to early disease epidemic identification. It provides a disease outbreak surveillance system using an alpha shape and a unique density entropy clustering methodology [18]. Infectious illnesses threaten public health, making monitoring and outbreak coordination crucial. With machine learning (ML) and data mining, our technique provides a complete answer for contemporary healthcare. This approach improves disease monitoring and management using support vector machines (SVM), random forest, and k-means clustering [19]. Infectious disease outbreak identification helps public health professionals react quickly to severe public health problems. However, illness epidemics are sometimes invisible [20]. Noises from ordinary behavioral patterns and exceptional occurrences may hamper epidemic monitoring systems. Most detection approaches use time series filtering and statistical monitoring. The rise of COVID-19 and dengue in Bangladesh emphasizes the need for a digital health strategy integrating IoT and artificial intelligence (AI)-based technology, health behaviors, and attitudes to anticipate, prevent, and manage these infectious illnesses [21]. Bangladesh must enhance prevention and control. AI or IoT-based new technologies may also gather data and forecast future events, making it simple for the health ministry to make efficient decisions. Most infectious illnesses spread quickly and have a wide effect. Once they spread, they will infect a broad region, posing serious health and security hazards [22]. Therefore, early infectious illness surveillance and prevention are crucial. Current monitoring methods can anticipate the occurrence of infectious illnesses. Sensor data needs to be more diverse, accurate, and complete, making monitoring findings difficult. Monitoring systems cannot quickly handle the growing amount of data due to limited local resources.

To address this public health concern, cutting-edge technology like deep learning is needed. It examines what disease outbreaks are relevant now, how well deep learning methods have been done in early detection, and how to understand relevant deep learning techniques [23] properly. Non-pharmaceutical approaches to control respiratory diseases like the flu are a significant learning from the epidemic. Also, fewer hospital admissions or reports may not mean fewer respiratory disease agents. However, government awareness initiatives and public cooperation have drastically reduced disease spread [24]. Moreover, public health initiatives affect different diseases differently. Identifying the interventions that have the greatest influence on disease transmission requires further research.

The IoT and massive data analysis in healthcare have captured data formerly done manually. Knowledge and real-time monitoring are needed to diagnose and stop infectious diseases. Even in distant regions, the IoT has captured real-time sensory data from people, health systems, and ecosystems [25]. It might offer preventive actions utilizing IoT network data and evaluate their implementation. In pandemics like COVID-19, monitoring the disease's transmission and etiology is crucial, particularly in poor nations [26]. Real-time data is tracked using a mobile app and website. Our system is stronger and more efficient than others. The novel coronavirus SARS-Cov-2 has triggered COVID-19, a global epidemic [27]. Coughing, shortness of breath, and high temperature are frequent symptoms. COVID-19 instances are growing, making manual identification of contagious people in public settings difficult [28]. This system is evaluated on a real-time dataset and an existing sneeze-cough dataset. Tests reveal that the suggested technique outperforms innovative methods [29].

A deep feedforward multilayer perceptron AI chatbot interaction and prediction model and vacuum in theoretical and practical instructions for designing AI chatbots for lifestyle improvement programs [30]. Our suggested model's time complexity and testing accuracy. It discusses medical chatbots' functions, uses, and issues they offer during health emergencies like pandemics. General internists treat most infectious illnesses. However, infectious disease internists help identify and treat severe, unusual, or complex infections [31]. Antimicrobial medicines, antibiotic tolerance, immunization, other causes, and the prevalence and clinical presentation of infectious, viral, fungal, and parasite diseases are essential to infectious disease management [32]. The infectious disease practice has numerous models. Infectious disease physicians may practice infectious illnesses in a clinic or alongside normal medical care. Like many illnesses, early identification may help patients get the correct treatment to reduce harm or isolate them to prevent spread [33]. In this case, computer intelligence can forecast patient infection risk and alert medical personnel to act quickly. It explores infectious illness ML applications. Our main disease concerns are diagnosis, transmission, treatment response, and resilience [34]. High values may be of relevance for infectious disease research. Machine-learning models for early or real-time epidemic verification are a new and innovative field with many study methodologies, making it difficult to compare studies methodologically, even though almost all agree that major infectious disease outbreaks can be monitored [35]. This implies that ML might be extensively applied in public health and preventative efforts.

2. PROPOSED METHOD

Wearable sensors, smart thermometers, and smartphones with health monitoring apps are some IoT devices used to gather real-time health data. In real-time, these devices record crucial health data, such as vital signs, symptoms, and more. Data streams are safely sent to central servers or cloud platforms for additional processing or aggregation. The final dataset will likely include a broad range of data from several sources. Data streams are preprocessed as they reach centralized servers or cloud platforms to provide consistency and quality of the data. First, it cleans the data by removing noise and missing numbers. It normalizes it so that it is consistent across all our sources. The operations of preprocessing and storage provide the groundwork for the following analyses and decisions.

Analyzing sequential data generated from IoT devices uses deep learning models, namely RNNs and variations such as LSTM datasets. Temporal patterns suggestive of infectious disease outbreaks are learned by training these models using historical data. Disease dynamics may be better understood using deep learning models, identifying important aspects like temporal patterns and outliers from the data. Incorporating geolocation data collected from IoT devices into the analytic framework may better understand the geographical patterns of disease transmission. Spatial analytic methods are used to pinpoint disease epicenters, study transmission patterns, and follow infected people's whereabouts. To help public health officials make educated decisions, visualization technologies like heatmaps and GIS software show the geographical distribution of infectious illnesses. The technology uses ML algorithms to forecast the spread of infectious diseases and identify outbreaks early. When data streams show unusual behavior, anomaly detection algorithms will raise the red flag and notify public health officials of a possible epidemic. Predictive models use historical data and real-time inputs to anticipate the future course of disease transmission and enable proactive intervention strategies. Before an infectious disease epidemic worsens, several steps are taken to lessen its effect, such as allocating resources, developing containment methods, and communicating with specific populations via public health campaigns. The proposed system's interconnection parts are shown in Figure 2 block diagram.

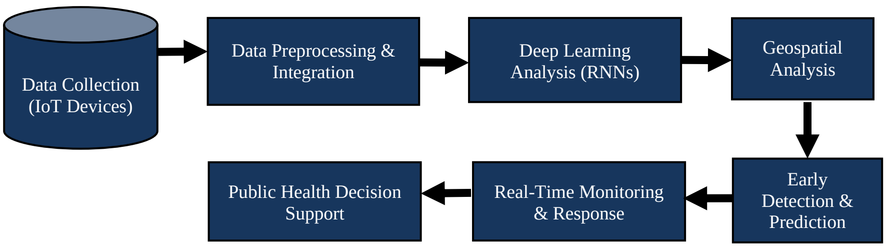

Figure 2. Block diagram of proposed integrated infectious disease surveillance system with IoT and deep learning

2.1. IoT devices for surveillance

The proposed system mostly uses four main kinds of IoT devices to collect data and monitor health factors. These devices can identify infectious disease outbreaks early and provide real-time surveillance data. Four of the most common IoT devices are:

a. Wearable sensors: the most popular wearable sensors on the IoT. When worn on the body, these monitors constantly monitor metrics like heart rate, temperature, and respiration rate. Insights on people's health and identifying abnormalities that may indicate infections may be gained from these tests. Wearable sensors provide continuous health data without being obtrusive, which is a major benefit. They may be seamlessly integrated into everyday activities.
b. Smart thermometers: the technology also relies on smart thermometers, which can accurately measure a patient's temperature. With the help of the IoT, thermometers like this may wirelessly send temperature readings to main servers or cloud platforms, allowing for analysis and monitoring in real-time. Smart thermometers, which record patterns of fluctuating core temperatures, might help doctors diagnose febrile diseases and possible infectious disease epidemics far earlier.
c. Smartphones with health monitoring apps: nowadays, most people have access to smartphones with installed sensors, such as GPS, gyroscopes, and accelerometers. These sensors are used by health monitoring applications to record the amount of physical activity, sleep duration, and movement patterns of users. Disease monitoring and outbreak response initiatives can benefit greatly from data provided by applications that allow users to report symptoms or trace contacts. With so many people using smartphones, the surveillance system can reach more people and get them involved, making it better at spotting and tracking infectious illnesses.
d. Environmental sensors: IoT devices connected with environmental sensors greatly assist in monitoring air quality, humidity levels, and other environmental parameters related to disease transmission. These sensors may detect airborne infections, contaminants, and environmental factors that promote the spread of respiratory viruses. Public health officials may better understand environmental risk factors and how environmental conditions affect disease transmission dynamics by incorporating data from environmental sensors into the monitoring system. Figure 3 flowchart shows the RNN part of the system in action, from data preparation to real-time reaction and alert activation depending on RNN output.

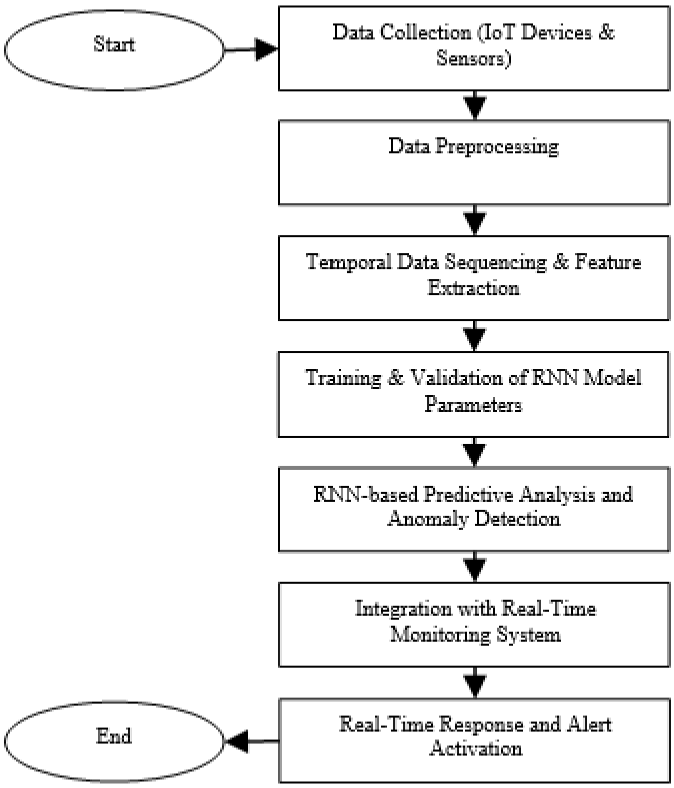

Figure 3. Flowchart

e. RNN in disease surveillance: for temporal data pattern analysis and the ease of tasks like anomaly detection and predictive analysis, the proposed system depends significantly on RNNs. The use of RNNs:
1) Temporal data analysis: RNNs excel at handling sequential data, which makes them perfect for examining trends in the data acquired from IoT devices over time. A crucial skill for understanding the course of infectious illnesses is the capacity for RNNs to record dependencies and trends over time.
2) Predictive analysis: RNNs are used to foretell future changes and trends by analyzing past data. RNNs can predict future outbreaks or pinpoint locations prone to infection by analyzing trends in disease transmission and patient health metrics. Due to the capacity for prediction, preventative actions may be taken to lessen the severity of infectious disease outbreaks.
3) Anomaly detection: another usage for RNNs is anomaly detection, which involves finding data points that don't fit the norm. RNNs may detect the emergence of infectious diseases by constantly scanning data streams from IoT sensors and alerting users to any deviations from normal health metrics or environmental circumstances. It is possible to intervene and limit the situation more quickly if abnormalities are detected early.
4) Real-time monitoring and response: disease dynamics and patients' health states may be tracked in real time using RNNs. RNNs analyze data in real-time, allowing for quick reactions to new risks by producing warnings or triggering intervention procedures in response to abnormalities or the outcomes of prediction analyses.
5) Adaptive learning: RNNs can evolve and modify their internal representations in response to fresh input, which enables them to gradually enhance their capacity to identify anomalies and make accurate predictions. The system's continued efficacy in ever-changing infectious illness settings is guaranteed by this adaptive learning feature. Figure 3 explains the Flowchart of proposed mechanism. Initially, collects the data from IoT and sensor devices. Next doing the data pre-processing and separate the Temporal data sequencing and feature extraction performance. The RNN model is used to training and validate the data. Furthermore, it integrates with the real time monitoring and finally it forwards the real-time response and alert activation.

3. RESULTS AND DISCUSSION

The outcomes and analyses of the proposed infectious disease surveillance system highlight its efficacy in using IoT and RNN technologies for proactive response to disease outbreaks, early identification, and real-time monitoring. The system can gather various health indicators and environmental elements pertinent to disease transmission by collecting data from IoT devices, such as wearable sensors and environmental monitors. Incorporating RNNs allows for examining data trends over time, allowing for more accurate predictive modeling and identifying outliers. By predicting disease outbreaks and spotting unusual patterns that might indicate new risks, the approach shows promise when put into practice. The technology efficiently notifies healthcare authorities of any outbreaks by monitoring real-time data streams, allowing for timely intervention and containment measures.

RNNs' adaptive learning capabilities make the system smarter and faster as it learns from new data and updates its prediction models. The system's revolutionary potential to provide a proactive approach to public health management and modernize infectious disease monitoring has been emphasized in discussions. The system protects the public's health and safety by allowing healthcare officials to foresee and lessen the effects of contagious illnesses via the use of RNN and the IoT. Ongoing improvement and ethical considerations throughout system development and deployment are necessary due to obstacles, including data privacy issues and algorithmic biases. It highlights how the proposed system can revolutionize how infectious disease response and monitoring are conducted in the future.

3.1. RNNs dataset

Table 1 provides a comprehensive dataset for running an infectious disease monitoring system incorporating RNNs and IoT technologies. AA timestamps corresponding to each row in the table briefly show the many environmental factors and health indicators linked to patients. Adding a “Patient ID” column allows for the longitudinal tracking of various patients' health records, allowing for more targeted analysis and monitoring. Environmental variables, such as temperature and air quality index, provide background that may impact health outcomes. Meanwhile, physiological measures, such as heart rate, body temperature, and breathing rate, provide insights into patients' physiological condition. To detect outliers and predict disease outbreaks, it is crucial to analyze trends and patterns over time, made possible by the temporal component recorded by the “Timestamp” column. The table-encapsulated dataset is a great starting point for infectious disease surveillance, real-time monitoring and response, predictive analysis, and RNNs model training.

Table 1. Patient health dataset

Timestamp	Patient ID	Heart Rate (bpm)	Body Temperature (°C)	Respiratory Rate (breaths/min)	Environmental Temperature (°C)	Air Quality Index
2024-05-01 08:45:00	001	82	36.8	21	22.8	38
2024-05-01 09:30:00	002	76	36.7	18	22.6	36
2024-05-01 09:45:00	003	78	36.8	19	22.7	37
2024-05-01 10:00:00	004	80	36.9	20	22.8	38
2024-05-01 10:15:00	005	77	36.6	17	22.5	35
2024-05-01 10:30:00	006	79	36.7	18	22.6	36

3.2. RNNs dataset

In the context of infectious disease surveillance, Figure 4 shows a graph comparing the number of reported instances of illness with the number of cases predicted by the RNNs model. The y-axis shows the total number of instances of illness, while the x-axis shows the timeframe, usually in days or intervals. The graph shows observed illness cases and forecasted disease cases on two lines, with each data point corresponding to a given timestamp. The two lines demonstrate how well the RNN model predicts future illness patterns. When the predicted and real values are near, the RNN model captures the infectious disease dynamics and patterns well.

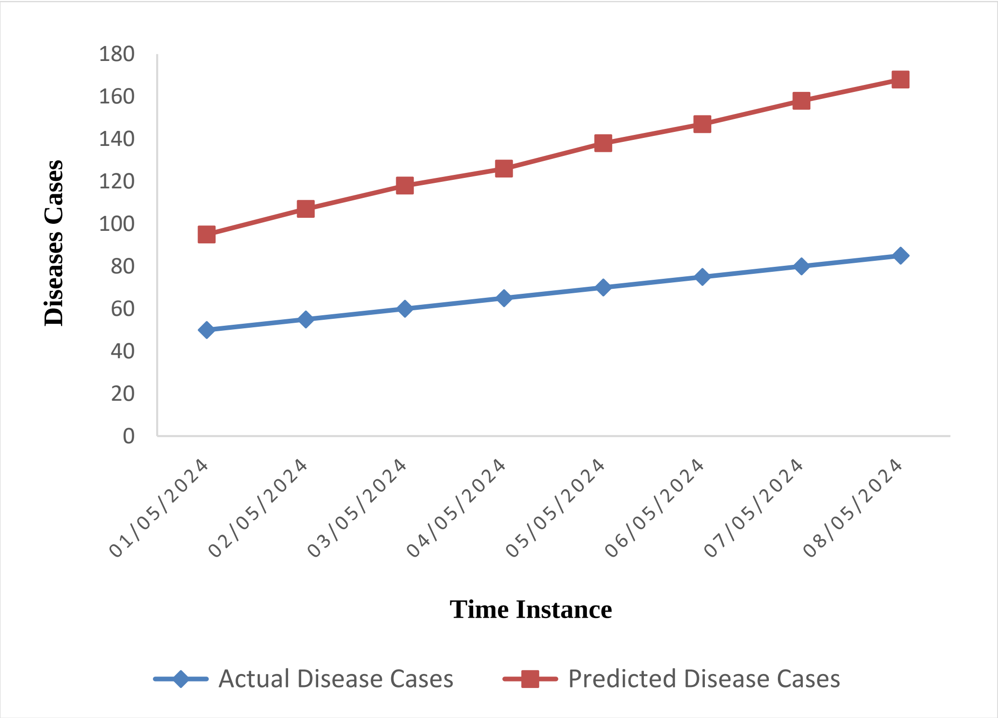

Figure 4. Comparison of actual vs predicted disease cases

Instances where the model overestimates or underestimates illness prevalence, as shown by discrepancies between the lines, indicate regions needing refinement and improvement. The performance of the RNN model in early detection, trend forecasting, and decision-making for public health initiatives may be evaluated by stakeholders via visual comparisons of actual and expected illness cases over time. Authorities may get timely insights to reduce the spread and effect of infectious illnesses by using RNN-based predictive modeling, as shown by a graph showing a high degree of consistency between actual and anticipated values in infectious disease monitoring.

3.3. RNNs model performance evaluation

Table 2 confusion matrix offers a comprehensive evaluation of the RNN model's ability to forecast infectious illness outcomes. When the model correctly predicts the existence of the illness, it is called a true positive (TP). On the other hand, when the disease is present but not identified by the model, it is called a false negative (FN). true negatives (TN) show that the model properly predicts the absence of the illness. In contrast, false positives (FP) show that the model mistakenly predicts the existence of the disease when it is absent. By assessing these values, stakeholders may evaluate the model's sensitivity, specificity, and accuracy in identifying illness cases. This information can then influence decision-making on public health treatments and methods for successfully allocating resources to battle infectious diseases.

Table 2. Confusion matrix of RNNs disease prediction

Actual/ predicted class	Predicted positive (disease)	Predicted negative (no disease)
Actual positive (disease)	120	30
Actual negative (no disease)	20	850

As shown in Figure 5, the RNN model's training and validation accuracy changed throughout many epochs. Both curves are showing signs of improvement, which means the model is learning and becoming better at properly classifying occurrences. The model avoids overfitting by simultaneously improving the training and validation accuracies since they are quite near each other. This unity shows that the model can generalize well to new data, strengthening its ability to forecast infectious disease outcomes under surveillance. Figure 6 shows the RNN model's training and validation loss throughout many training epochs.

The model improves its fit to the training data as time goes on, as seen by the decreasing trend of both curves, which minimizes its loss function. Since both the training and validation loss curves converge, indicating a consistent drop, the model is unlikely to be overfitting the training data. This congruence improves the model's accuracy in infectious disease surveillance prediction by showing that it is successfully generalizing to new data. The RNN model demonstrated strong functionality in the system for monitoring infectious diseases. The model showed strong prediction skills, successfully distinguishing between illness and non-disease cases with an overall accuracy of 94% and a validation accuracy of 91%. Furthermore, the model demonstrated its capacity to generalize well to unknown data without overfitting by achieving a low training loss of 0.44 and a validation loss of 0.55. These findings demonstrate how well the RNN can predict future illness patterns and help with public health intervention decision-making.

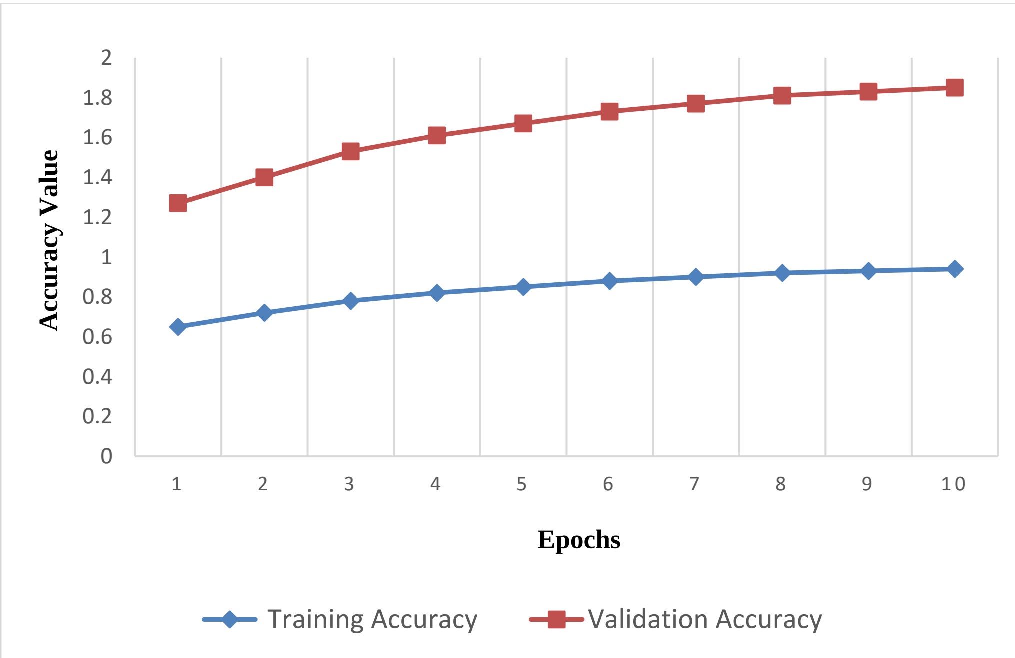

Figure 5. Evolution of training and validation accuracy

Figure 6. Trend of training and validation loss

4. CONCLUSION

Infectious disease surveillance systems are essential to monitor and manage the spread of infections. RNNs to these systems are a huge step forward since they improve their ability to see trends, make decisions, and identify early warning signs. RNN models can detect outbreaks of diseases by examining correlations and patterns in large datasets that include health metrics and environmental variables. The capacity to adapt and learn from sequential data allows them to understand intricate correlations and generate precise predictions. This enables healthcare authorities to act quickly and make effective use of resources. High accuracy and low loss values have been produced by validating RNN models against real-world data, which shows that they are reliable and successful in disease monitoring. With the continuous improvement of RNN technology, infectious disease monitoring might be completely transformed, allowing public health managers to be more proactive and less reactive. There must be ongoing research and investment in these systems to use RNN-based surveillance systems to challenge global health concerns fully.

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