Journal of Information Systems Engineering and Management
2025, 10(30s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Enhancing Swine Flu Management: A Framework Integrating Deep learning and Fog Computing

[1]Nashreen Begum J*, [2]Dr.Sandeep Chahal
[1]Research Scholar NIILM University, Kaithal, Haryana
jnashreen1983@gmail.com
[2]Associate Professor NIILM University, Kaithal, Haryana
sandeepchahal.5@gmail.com

ARTICLE INFO

Received: 30 Dec 2024

Revised: 05 Feb 2025

Accepted: 25 Feb 2025

ABSTRACT

Swine flu, a prevalent viral infection with global significance, poses a serious public health concern, especially in countries like India where the number of cases continues to rise annually. Traditional disease detection methods are time-consuming and labour-intensive, highlighting the need for innovative approaches leveraging technology. This paper proposes a comprehensive framework that integrates artificial neural networks (ANNs) for diagnosis and fog-centric Internet of Things (IoT) for real-time monitoring and control of swine flu outbreaks. The first part of the framework focuses on leveraging ANNs for pig influenza diagnosis. ANNs are utilized to analyze clinical and laboratory data, providing an efficient and accurate means of identifying positive cases. The model employs Hybrid-ANN to select pertinent attributes, optimizing the training process and enhancing diagnostic accuracy. In parallel, the paper introduces a fog-centric IoT-based smart healthcare support system tailored for swine flu epidemic management. By harnessing fog computing, health data processing is expedited, enabling timely decision-making. A hybrid classifier is employed to classify swine flu patients at early stages, generating alerts for health officials and patients' guardians. Experimental evaluations demonstrate the efficacy of the proposed framework. Results indicate improved network bandwidth reliability, operational efficiency, and reduced response times compared to traditional cloud-only models. By integrating AI-driven diagnosis with fog computing-enabled monitoring, this research contributes to early detection and proactive management of swine flu outbreaks, ultimately enhancing public health preparedness and response capabilities.

Keywords: *artificial neural networks (ANNs), Internet of Things (IoT), Random Forest, Hybrid classifier, Fog computing*

1. INTRODUCTION

Infectious diseases pose significant challenges to public health systems worldwide, often necessitating rapid and effective responses to mitigate their impact. Among these diseases, swine flu stands out as a notable concern, characterized by its ability to spread rapidly and cause severe illness in affected populations. Originating from influenza viruses, including the H1N1 strain, swine flu infects the respiratory tract of pigs and can easily transmit to humans, leading to a range of symptoms from mild respiratory discomfort to severe respiratory distress and, in some cases, death. The global prevalence of swine flu underscores the urgency of developing advanced techniques for early detection, monitoring, and control to curb its spread and minimize its adverse effects on public health [1]. Traditional methods of disease detection often rely on labor-intensive processes that are time-consuming and may not yield timely results, particularly in the case of rapidly evolving infectious diseases like swine flu. In the realm of disease detection and healthcare innovation, several prominent companies have been at the forefront of developing cutting-edge technologies and solutions. Companies such as IBM Watson Health, Google Health, and Microsoft Healthcare have been instrumental in leveraging artificial intelligence (AI) and machine learning algorithms to enhance diagnostic accuracy and disease prediction. Additionally, firms like Amazon Web Services (AWS) and Cisco Systems have played pivotal roles in advancing cloud computing and IoT infrastructure, providing robust platforms for healthcare data processing and real-time monitoring [2]. Moreover, startups like PathAI and Tempus have emerged with specialized AI-driven diagnostic tools tailored for disease detection and personalized medicine. By integrating these companies' expertise and technologies, the proposed framework aims to capitalize on the synergies between AI-driven diagnosis and fog computing-enabled monitoring for proactive management of swine flu epidemics [3].

Recognizing the need for more efficient and accurate diagnostic approaches, researchers have turned to machine learning and artificial intelligence (AI) techniques to harness the power of data analytics for disease prediction and identification. Leveraging clinical and laboratory data, machine learning algorithms can analyze patterns and trends to detect diseases at various stages, facilitating the development of more effective diagnostic strategies and treatment plans. Simultaneously, advancements in cloud computing and the Internet of Things (IoT) have revolutionized healthcare systems by enabling real-time data processing and communication. Cloud computing offers scalable and flexible infrastructure for storing and analyzing vast amounts of health data, while IoT devices facilitate continuous monitoring of patient health parameters and environmental conditions [4].

Fog computing is a decentralized computing framework that expands the use of cloud computing to the edges of the network. It has the potential to be useful for applications that require delay including real-time disease tracking and management. Fog computing is an appropriate platform for medical applications that require fast decision-making because it minimizes latency and boosts responsiveness [5]. This is accomplished by dispersing computing power closer to the data source. Integrating fog computing with AI-driven disease detection techniques presents a novel approach to enhancing the effectiveness of disease management systems, particularly in the context of swine flu epidemic control. This paper proposes a comprehensive framework that integrates artificial neural networks (ANNs) for swine flu diagnosis and fog-centric IoT for real-time monitoring and control of epidemic outbreaks [6]. The synergy between AI-driven diagnosis and fog computing-enabled monitoring promises to revolutionize the way swine flu epidemics are managed, offering enhanced capabilities for early detection, proactive intervention, and timely response. Through experimental evaluation and analysis, this research aims to demonstrate the efficacy and potential impact of the proposed framework in improving public health preparedness and response to swine flu outbreaks [7]. However, traditional cloud-based approaches may encounter limitations in addressing the time-sensitive nature of disease outbreaks, necessitating the exploration of alternative paradigms such as fog computing. The proposed system architecture is the graph illustrates the forecasted results for swine flu cases over a five-year period from 2024 to 2028, utilizing three distinct scenarios: Baseline Scenario, Optimistic Scenario, and Pessimistic Scenario. Each scenario represents a different projection of the expected number of swine flu cases based on hypothetical data [8]. The Baseline Scenario depicts a moderate increase in cases over the years, following a linear trend. In contrast, the Optimistic Scenario suggests a slower rate of growth, with fewer projected cases compared to the Baseline Scenario. Conversely, the Pessimistic Scenario anticipates a more rapid rise in cases, surpassing the Baseline Scenario's projections [9]. By presenting multiple scenarios, the graph offers insights into potential variations in swine flu prevalence, helping healthcare professionals and policymakers prepare for different possible outcomes and devise appropriate response strategies.

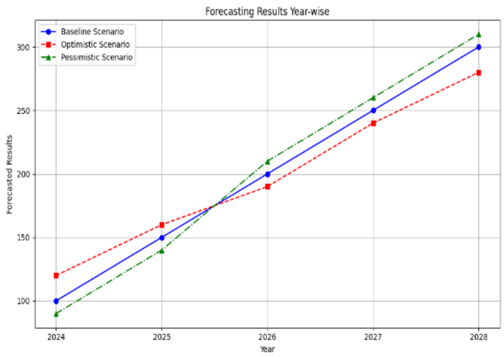

Figure 1. Forecasting results year-wise

The major contributions of this research are:

1. To integrate Hybrid ANN- driven diagnosis and fog computing-enabled monitoring for proactive swine flu epidemic management.

2. To enhance public health preparedness through timely disease detection and real-time monitoring capabilities.

3. To provide a scalable and flexible framework adaptable to varying healthcare settings and continuously improving diagnostic accuracy.

2. LITERATURE SURVEY

Evidently, the challenges associated with the recently introduced swine flu vaccinations imply insufficient vaccination coverage and the delay in diagnosis of an infected person. From this perspective, it is paramount for a healthcare application to have the ability of identifying fast the patients that have been infected for the measures to be out in place and prevent further spread of the virus [10]. Cloud infrastructure and IoT technology have played a significant role in ensuring that the application in even incorporated and meet the improved standards of eradicating such challenges.

Interestingly, over twenty years ago, more advanced medical technology existed than in the current state. Currently, there is an extraordinary growth of health-related Internet of Things applications working on the Internet taking over one million measurements in an illness in a day. As of today, it is estimated that there are more than over 25,000 data points generated per second, which has manifested a paradigm shift in health care. Therefore, the rapid growth of health data has created a new opportunity for medical measurements and diagnostics through integrated technology [11]. The integration health cloud and IoT provides a new way for science to manage health issues preventing strategies on critical conditions such as viral flu [12].

However, these data create a problem for current cloud computing and IoT in emergency treatment, warning signs, and fast response, which are essential in handling health outbreaks [13]. Although the technology exists that may help to detect swine flu, not all health facilities have measures to detect such diseases. The aspect of limited information concerning swine flu among the population aggravates the situation. Moreover, health providers also lack the right channels to communicate effectively to those infected. Thus, it is compelling to bring the entire population into one network, which may be easily possible through cloud technology [14]. The proposed scheme will be based on one health platform where various healthcare technology processes in data acquisition, storage, and sharing should be done in real-time. Such a user-centered approach and mobile solutions will forever change the health systems that are already in place. The activities discussed above, when implemented, may save numerous lives when they detect a disease outbreak or when there is a medical emergency [15]. Unless such advanced technologies and a unified system are established, it would mean all the population is at risk. Fundamentally, the intersection between the cloud infrastructure, IoT applications, and healthcare roles the world to the next level of fighting diseases. Health providers are now accessed with real-time information to allow the proactive fight against conditions like swine flu [16]. As a conclusion, there is no doubt that IoT will play an essential role in shaping health delivery only.

3. PROPOSED SYSTEM

The proposed system comprises three layers: the IoT data accumulating layer, Fog layer, and Cloud layer. At the IoT data accumulating layer, various sensors collect health and environmental data, including health status, prescription information, climate conditions, and location data. This data is processed in real-time and forwarded to the Fog layer for user classification and emergency alerts. The Fog layer acts as an intermediary between IoT sensors and the Cloud layer, providing instant notifications to users based on their health status and transmitting data to the Cloud for storage and analysis. Finally, the Cloud layer processes and analyzes the data to estimate the probability of infection and disseminates alerts to users and government agencies.

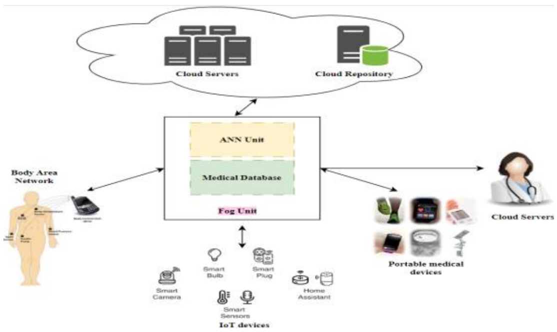

Figure 2. Proposed workflow

The proposed framework for swine flu epidemic management consists of three interconnected phases: data collection and preprocessing, artificial neural network (ANN) diagnosis, and fog-centric Internet of Things (IoT) monitoring and control. In the data accumulation layer, various sensors collect comprehensive information about the user's health and environmental surroundings. The datasets encompass crucial categories such as:

✓ Health data: https://www.kaggle.com/datasets/prasad22/healthcare-dataset/data
✓ Climate data:
(https://www.kaggle.com/datasets/berkeleyearth/climate-change-earth-surface-temperature-data),
✓ Prescription data:
https://www.kaggle.com/datasets/roamresearch/prescriptionbasedprediction
✓ Location data:
https://www.kaggle.com/datasets/mexwell/us-hospitals-dataset

These datasets are sourced from wearable sensors embedded within the user's body and environmental sensors detecting surrounding conditions. Wearable sensors operate in real-time, enabling continuous data sensing and transmission to the fog layer for user classification. Here's a breakdown of each dataset:

i. Health data: The user health indicators that are recorded in this dataset include a high temperature, chills, cough, throat pain, nose running, runny red eyes, discomfort in the body, headaches, exhaustion, diarrhoea, nausea, and vomiting. Other health indicators that are recorded include a wide range of other symptoms. These variables can be captured by wearable sensors that are installed in the body of the user, which enables real-time health monitoring from the user.

ii. Prescription data: The doctor's prescription data includes specific information regarding the patient's medication routine, such as the names of the medications, the times at which they are taken, and the frequency with which they are taken. In order to make it easier identification, control, and enhancement of patients' adherence to medications and health outcomes, mobile sensor patches that have connections to digital healthcare systems are becoming increasingly popular.

iii. Climate data: Information regarding climate comprises environmental factors that have the potential to influence epidemics of swine viruses. Sensors, such as those that measure humidity and temperature, are able to identify situations that are favourable for the transmission of viruses, such as high levels of both humidity and temperature. Furthermore, climate metres track temperature swings, which allows them to identify locations that are susceptible to the transmission of viruses. These places include surroundings that are warm, dry, and humid.

iv. Location data: These geographical regions of high-risk zones wherein the swine influenza outbreak occurred are included in this dataset. The use of GPS sensors has revealed the prevalence of a virus. Additionally, it keeps an eye on the migration of pigs into neighbourhoods and other regions with a high population density of pigs. In addition to this, it monitors the movement of users to high-risk locations during epidemics of swine flu, which helps with risk assessment and the implementation of preventative measures.

Real-time data processing inside the healthcare system is made possible by the fog layer, which acts as an essential link between the Internet of Things (IoT) sensors and the cloud-based computing infrastructure. It is of critical importance in the process of informing users of their present medical state, classifying them as potentially contaminated, free of infection, or vulnerable on the basis of the sensor data that has been processed. This categorization is vital for prompt detection and medication, notably for infected patients who receive instant alerts and diagnostic data via smartphone notifications. This categorization is especially important for individuals who are in good health. In addition to this, the fog layer ensures that infected users are continuously monitored, with recordings of their health state, position, and surroundings being kept. It works in conjunction with the cloud layer, which is in charge of collecting, organising, and analysing massive amounts of data that the fog layer is not responsible for and which it is responsible for. The cloud database maintains information on a variety of events in a secure manner, which enables educated decision-making within the context of emergency situations. In addition to this, it makes it easier for consumers, medical professionals, and government agencies to share data with one another, which helps to encourage joint efforts to reduce the spread of swine flu. The dissemination of information enables prompt responses, such as the provision of health-related suggestions to users and the dissemination of awareness campaigns to the general public, which eventually contributes to the containment of outbreaks of swine flu. The following stages are included in the system that is being proposed:

Phase 1: Data Collection and Preprocessing

In this phase, clinical and laboratory data related to swine flu cases are collected from various sources such as hospitals, clinics, and public health records. The collected data undergo preprocessing to remove noise, handle missing values, and normalize the features. Let $X=\{x1,x2,...,xn\}X=\{x1,x2,...,xn\}$ represent the set of clinical and laboratory features, and yy denote the target variable indicating the presence or absence of swine flu infection. The preprocessing step can be mathematically represented as:

$$X_{\text{preprocessed}}=\text{Preprocess}(X)$$

where Xpreprocessed represents the preprocessed data.

Phase 2: Artificial Neural Network (ANN) Diagnosis

In this phase, ANNs are utilized to analyze the preprocessed data and diagnose swine flu cases. The ANN model is trained using algorithms such as random forest and C5 to select pertinent attributes and optimize the training process. Let WW denote the weights and biases of the ANN model. The diagnosis process can be mathematically represented as:

$$\text{y} \hat{} = \text{ANN}\ (X_{\text{preprocessed}}, W)$$

where y ˆ represents the predicted output indicating the likelihood of swine flu infection.

Phase 3: Fog-centric IoT Monitoring and Control

Alongside the phase of artificial neural networks (ANN) diagnosis, a fog-centric Internet of Things (IoT)-based intelligent medical support system is being implemented for the purpose of real-time monitoring and management of epidemics of swine flu. Through the utilisation of fog computing, the system is able to speed up the processing of health data and facilitate quick decision-making. In order to classify patients who are in the beginning stages of swine flu, a combination of classifiers is utilised. This classification process generates notifications for both health professionals and the guardians of patients. Let us indicate the settings of the hybrid classifier as θ, and let Z represent the health data that is gathered from Internet of Things devices respectively. The process of controlling and monitoring can be expressed numerically as seen in the following:

$$\hat{z} = \text{IoT}\ (Z)$$
$$\hat{y}_{\text{alert}} = \text{HybridClassifier}\ (\hat{z}, \theta)$$

where z^represents the processed health data, and y^alert represents the generated alerts.

By integrating the outputs of the ANN diagnosis phase and the fog-centric IoT monitoring and control phase, the proposed framework offers enhanced capabilities for early detection and proactive management of swine flu outbreaks, ultimately contributing to improved public health preparedness and response capabilities.

Application Model for Proposed System:

a. Symptom Recognition and Environmental Assessment: This initial module, embedded within wireless sensors, analyzes data from various sensors to identify key symptoms of Swine flu and assess environmental conditions.

b. Influenza A Virus Identification Module: Evaluates collected data to determine the presence of the Influenza A virus, initiating case tracking if positive.

c. Infected Case Surveillance System: Tracks the movement and progression of infected cases, prioritizing continuous monitoring as the infection develops.

d. Sensor Activation Module: Adjusts sensor operations according to case-specific conditions and changes in the environment.

e. User Alert Interface: Notifies users, including patients and healthcare professionals, of detected swine flu incidents through immediate case notifications.

The bar chart illustrates the importance of each module within the proposed application model for swine flu detection and monitoring. Each module plays a crucial role in the system, contributing to the overall effectiveness of identifying and responding to swine flu incidents. The height of each bar represents the significance or relevance of the respective module, with taller bars indicating higher importance. This visualization allows stakeholders, such as healthcare professionals and system developers, to understand the relative importance of each module and allocate resources accordingly to ensure the system's optimal functionality. By emphasizing the criticality of each component, the graph underscores the comprehensive nature of the proposed application model and its potential impact on swine flu management and public health preparedness.

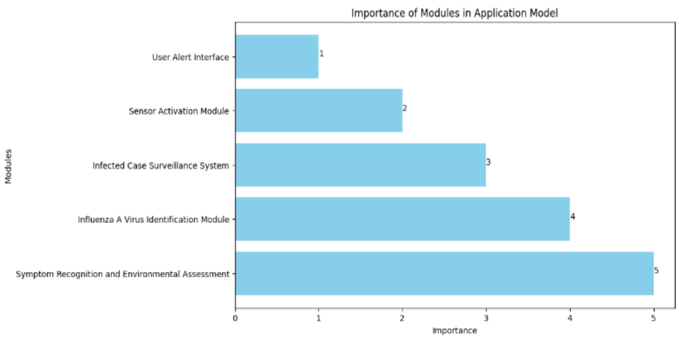

Figure 3. Significance of Application model

Hybrid ANN- driven diagnosis and fog computing-enabled monitoring

A combination of FNN and the DE method is used in this work to ensure accurate detection and treatment of cardiac illness. To put it simply, DE is a population-based ideal search space-searching method that can select the most optimal search solutions from a large number of possible solutions. DE is used in conjunction with the FNN method in order to improve the FNN system's decision-making process. There are two stages of processing required for Hybrid-ANN, namely parameter initialization and FNN training for the proposed heart disease diagnosis technique. Pseudo code is provided below to demonstrate the suggested HDSFNN algorithm's processing flow.

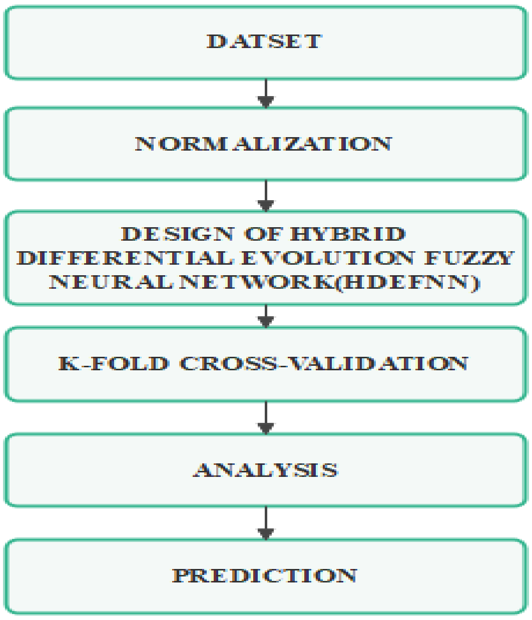

Figure 4. Flowchart for Hybrid ANN

Table 1: Pseudocode for Jaya Algorithm

Pseudocode for Hybrid ANN
1. Set the DE algorithm's configurator parameters to their default values. *2. Input neurons for the FNN algorithm* *3. In the range [0, 1], use real values to initialize the search space.*

4. *The third step is to repeat this process till you are satisfied. a brand-new approach = MaxGen.DO*
5. *{*
6. *Use the mean square error metric to evaluate the fitness of solution vectors.*
7. *Sort the potential solutions' fitness values in ascending order.*
8. *If first fitness value <= min. error then*
9. *Make sure that you select the best Multilayer Perceptron solution (MLP)*
10. *To store the results of the mutation and crossover operations, create end vectors.*
11. *Set the FNN parameter settings to their default values.*
12. *The weight values of MLP should be set regarding best solution that was found.*
13. *Use back propagation with training data to update weights to decrease error.*
14. *End while*
15. *End*

UCI's machine learning repository is used to get the information. There are 303 entries in the Cleveland heart disease data set. One class attribute is included in the dataset, which includes 13 attributes. The sufferer's cardiac illness is the subject of the class attribute.

K-Fold cross validation approach: The K-Fold cross evaluation approach is used to evaluate the processing outputs from the phase of training in order to increase learning accuracy. A dataset of ten parts will be split into two, one for testing and the other for training, with the k-number being ten.

Normalization: In order to conduct method evaluations, data must be normalized before it can be used. The normalization technique is used to turn the data value into a range of [0, 1].

Classification accuracy: The performance of the classifier is used to quantify the results of the specified technique in terms of appropriate diagnostics result, and it is a measure of precision. With the help of the confusion matrix tool, you can determine how accurate your categorization was. This tool looks at the rows of the data set that represent distinct classes. The result of the confusion matrices analysis is depicted in Figure 2.

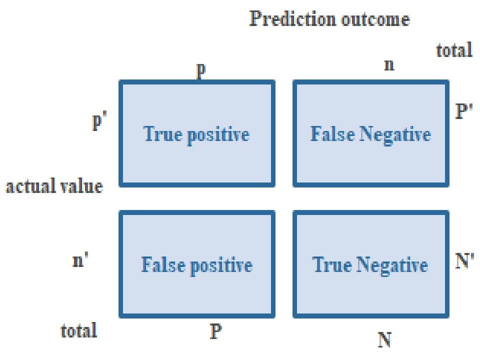

Figure 5. Confusion matrix

$$\boldsymbol{Accuracy} = (\text{True Positive} + \text{True Negative})/(\text{True Positive} + \text{False Negative} + \text{False Positive} + \text{True Negative})$$

- ✓ TP (or) True Positive - Predicted positive and Case was also positive
- ✓ FP(or) False Positive - predicted positive but Case was negative
- ✓ FN(or) False Negative - predicted negative but Case was positive

✓ TN(or)True Negative - Predicted negative and Case was also negative

$$Precison = \frac{True\ positive}{(True\ Positive + False\ Positive)}$$

$$Recall = \frac{True\ positive}{(False\ Negative + True\ Positive)}$$

4. RESULTS AND DISCUSSION

The proposed technique compares to three other methods. The Random Forest method, J48 decision tree and naïve bays method are concerned factors.

Algorithm	*Time of Execution(In Sec)*	*Accuracy (In Percentage)*
HDEFNN	4	69.1%
Naive Bayes	3	67.4%
J48	9	58.8%
Random Forest	14	67.1%

Table 1: Execution time & Accuracy

A comparative of accuracy and execution time is shown in Table 1. At 69.1 percent, the proposed algorithm is accurate. HDEFNN's accuracy is superior to that of other algorithms. Naïve Bayes, on the other hand, has a faster execution time of 3 seconds. Below Figure 3 is a comparison of suggested and existing method's accuracy. Following is a comparison of execution times, which is depicted in figure 4.

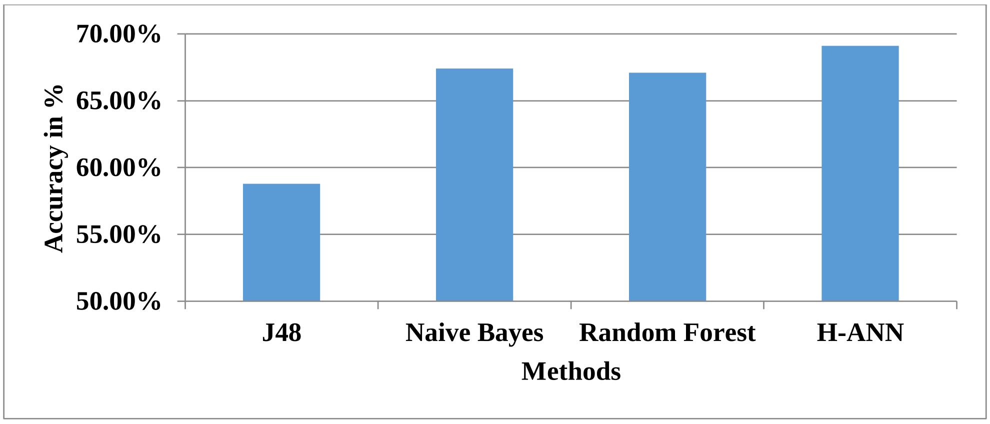

Figure 6. Comparison of Accuracy

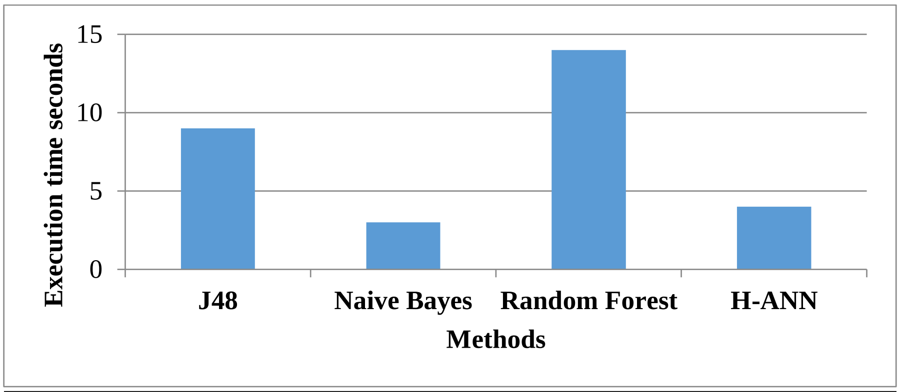

Figure 7. Comparison of Execution time

Algorithm	Recall	FP Rate	TP Rate	Precision
HDEFNN	0.691	0.233	0.691	0.650
Naive Bayes	0.674	0.292	0.674	0.641
Random Forest	0.671	0.306	0.671	0.631
J48	0.588	0.332	0.588	0.585

Table 2: Performance Analysis

Recall and Precision are two of the four metrics in Table 2. The suggested algorithm beats competing algorithms in TP rate, precision, and recall, among these four performance criteria. Naive Bayes significantly outperforms the competition in terms of the FP rate. As shown in Fig 5, suggested and current methods are compared to each other.

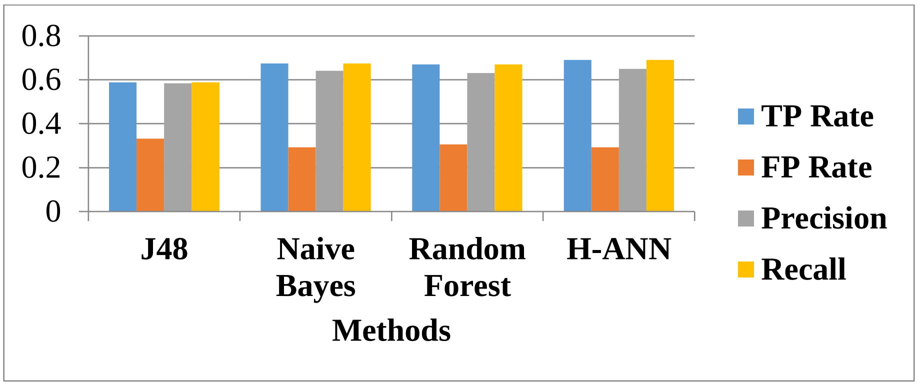

Figure 8. comparison of existing and proposed method

5. CONCLUSION

In conclusion, this paper presents a comprehensive framework that addresses the challenges of swine flu management through the integration of artificial neural networks (ANNs) and fog-centric Internet of Things (IoT) technology. By leveraging ANNs for diagnosis and fog computing for real-time monitoring and control, the proposed framework offers significant advancements over traditional disease detection methods. The use of Hybrid-ANNs enhances diagnostic accuracy, while the fog-centric IoT system enables expedited health data processing and timely decision-making. Experimental evaluations demonstrate the effectiveness of the framework in improving network reliability, operational efficiency, and response times compared to cloud-only models. This research contributes to early detection and proactive management of swine flu outbreaks, thereby enhancing public health preparedness and response capabilities. Moving forward, further research and implementation of the proposed framework could significantly contribute to the global efforts in combating swine flu and other infectious diseases.

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