Research Article

Using Sequence Mining to Predict Complex Systems: A Case Study in Influenza Epidemics

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According to the World Health Organisation, three to five million individuals are infected by influenza, and around 250,000 to 500,000 people die of this infectious disease worldwide. Influenza epidemics pose a serious public health threat. Moreover, graver dangers are encountered with influenza subtypes against which there is little or no preexisting human immunity. Such subtypes of influenza have the potential to cause devastating epidemics. Thus, enhancing surveillance systems for the purpose of detecting influenza epidemics in an early stage can quicken response times and save millions of lives. This paper presents three adapting intelligence models: support vector machine regression (SVMR), artificial neural network using particle swarm optimisation (ANNPSO), and our intelligent time series (INTS) to predict influenza epidemics. The novelty of the current study is that it proposes a new intelligent model to predict influenza outbreaks. The INTS model combines clustering with a time series model to enhance the prediction of influenza outbreaks. The innovation of our proposed model integrates the results obtained from the existing weighted exponential smoothing model with centroids obtained from clustering. We developed a surveillance system for influenza epidemics using Google search queries. The current research is based on a weighted version of the Center for Disease Control and Prevention influenza-like illness activity level obtained from the Center for Disease Control and Prevention data, as well as query data obtained from the Goggle search engine in the USA. The influenza-like illness data was collected from January 4, 2009 (week 1), to December 27, 2015 (week 52), stretching across a total time span of 312 weeks. Google Correlate was used to select search queries related to influenza epidemics. In total, 100 search queries were obtained from Google Correlate, 10 of which were better and more relevant search queries selected in this study. The model was evaluated using online Google search queries collected from Google Correlate. Standard measure performance MSE, RMSE, and MAE were employed to estimate the results of the proposed model. The empirical results of the INTS model showed MSE = 0.003, RMSE = 0.036, and MAE = 0.0185, indicating that the errors of the proposed model are very limited. A comparative model of predicting results between the INTS model, alternative Google Flu Trend (GFT), and autoregression with Google search data is also presented. The proposed model outperformed the existing models.

1. Introduction

With the rapid development of societies and economies worldwide, health technologies have been enhanced, and health facilities have been promoted as well. The flu infection faces societies with a number of health problems. Consequently, influenza diseases have still posed a great threat to human health, and controlling influenza diseases has become a very important challenge globally. Influenza has brought huge losses to national economies and continues to pose a serious threat to human health across the world. Although the subtypes of influenza diseases, such as
smallpox and malaria, have been efficiently controlled, the seasonal incidences of influenza still have high occurrence rates and cause many emergent health problems, including early deaths worldwide [1].

Therefore, influenza is the first infectious disease for which a surveillance system was implemented. Yet, its effective control remains elusive. Millions of Internet users around the world have submitted Internet search terms for the purpose of developing a system to detect influenza outbreaks at the earliest stages [2, 3]. The rapid adoption of the Internet has opened new gates for developing and enhancing healthcare. Many researchers have used huge amounts of data on the Internet and social media platforms such as Twitter or Facebook to discover novel methods to diagnose diseases. Thus, the language patterns from the Internet and social media have proved their usefulness in analysing and predicting chronic diseases and in determining the behaviours and habits that increase the possibility of those diseases. Understanding population behaviour and trends of noncommunicable diseases is directed by using web search activity data. Noncommunicable diseases have been detected by using web search activity data and examination data that has been submitted to the concerned health officials. These search activity data have the same trend as examination data [4, 5].

Researchers have compared Internet search query data relating to the main key adaptable risk factors of noncommunicable diseases with clinical population data from the US Center for Disease Control. Developing real-time surveillance can provide a proxy for clinical population data and real-time web search data for enhancing healthcare systems. Most previous research has tried to predict influenza disease using data from the Internet search query alone. Here, we developed a new model that has the capability to predict the influenza epidemic with the best accuracy.

The main contribution of this study is to propose a complex system that can assist in enhancing the time series models in the healthcare domain. The INtelligent Time Series (INTS) combines clustering with a time series mode. INTS model was developed to predict the influenza epidemic based on a Google search. We found that the INTS model is capable of yielding better results compared with another proposed model, such as Google Flu Trend (GFT) and Auto-Regression with Google search data (ARGO).

2. Background of the Study

Typically, the Internet is a primary tool that can identify individuals making attempts towards wellbeing and supplying data. Individuals are frequently subjected to certain infections or medicinal problems and always look for suitable medicinal medications or methods. Various studies have recommended remarkable methods for predicting influenza epidemics [6, 7]. In November 2008, Google launched the Google Flu service, which uses a computational search term model to predict influenza activity. In 2009, Google also offered Google Flu Trends (GFT), a digital method used to detect public health surveillance [8]. By gathering web information, the investigator claims to validly estimate influenza epidemics. The novelty of the GFT model is that it is used by the Center for Disease Control (CDC) to find specific search terms from digital data for predicting influenza epidemics. Various subsequent studies have modelled their approaches after the GFT model to enhance the GFT model [9–12].

Hence, we present the INtelligent Time Series (INTS) model, which outperforms all alternative models in predicting influenza epidemics by using Internet search queries. Increasing studies are focusing on monitoring data-based infectious illnesses to complement current technologies and develop new models [13–19]. Furthermore, developed models for detecting infectious diseases using Internet searches are presently being conducted by using large amounts of information, such as Internet search queries [20–24]. Thus, it becomes possible to collect and process Internet search information to monitor the healthcare system. Internet search information has the ability to detect an epidemic at a better speed than standard surveillance technologies, according to Towers et al. [25]. For instance, the model that included search query data obtained the best results when Huang et al. predicted hand, foot, and mouth disease using the generalized additive model (GAM). As such, fresh big data surveillance tools have been shown to have the benefit of easy accessibility and recognising patterns in infectious disease before formal organisations [26]. Social media provides big data for useful information that can help discover those patterns. Tenkanen et al. reported that big data on social media is comparatively simple to obtain useful information for developing a real-time system [27]. This proposed research uses Twitter information to forecast mental illness [28]. Besides the influenza epidemic, a new type of influenza virus against which there is no previous immunity shows human-to-human transmission and has caused millions of deaths until an epidemic vaccine has been discovered. This system can use search queries from Google’s search engine for influenza epidemic surveillance [29]. Quick and early estimation and prediction of the influenza epidemic before spreading greatly helps governments, health officials, and healthcare organisations to take appropriate decisions and timely prevention measures. In addition, influenza epidemic surveillance helps to provide information about the spread of influenza on a larger scale. Furthermore, the system helps in taking preemptive measures and spreading awareness regarding the disease to minimize its spread. The increased number of Internet users and researchers has helped identify Google’s search engine use as a new monitoring scheme to complement the traditional scheme. Thus, Google Flu Trend tracks Google queries for obtaining information linked to influenza behaviour by Google customers, which shows a correlation with influenza CDC data while providing a projection of 1 to 2 weeks before CDC releases. Researchers and developers have presented several techniques to accomplish real-time surveillance systems for controlling the spread of influenza. It has also been demonstrated that the attention methodology for widely enhancing the GFT model with digital disease detection shows a guaranteed value. The attention model chooses particular queries automatically to monitor the
updated influenza epidemic estimate system. Mauricio et al.
[30] collected Internet search terms from a clinician’s da-
tabase to forecast influenza activity. Santillana et al. [12]
demonstrated how an alternative methodology enhancing
the GFT model with guaranteed value for digital disease
detection is broadly employed. The alternative model au-
tomatically chooses exact query terms to monitor the up-
dates of the proposed model for estimating the influenza
epidemic. Kang et al. [31] and Milinovich et al. [32] have
developed a model to predict influenza activity by using
Internet search queries obtained from influenza surveillance
facilities in China. Milinovich et al. [33] presented a
framework to estimate infectious diseases in Australia by
using Internet search queries. They observed that web search
activities have a potential role in predicting emerging in-
fected disease events. Samantha Cook et al. [34] compared
their methodology to the GFT model for the estimation of
influenza incidences by using an Internet search. They
noticed that the model performed better than the GFT
model. Nsoesie et al. [35] and Chretien et al. [36] presented a
useful literature review of work in this area and described the
methodology and data that estimate and predict the influ-
zena epidemic. As they pointed out, some researchers used
search queries to forecast influenza outbreaks. Twitter,
Facebook, and Four Square are examples of sites where
individuals intentionally post updates on their daily be-
aviours, health status, and physical locations. Paul et al.
[37] used search queries from the social medium of Twitter
to improve influenza forecasting. They observed that tweets
were positively correlated with existing surveillance data
provided by the CDC. HarshavardhanAchreka et al. [38]
developed digital flu surveillance using Twitter data to es-
timate and predict the influenza epidemic. They argued that
tweets collected from the social medium of Twitter could
substantially help to detect influenza outbreaks earlier.
Aldhyani et al. [39] proposed the adaptive network fuzzy
inference system (ANFIS) model to predict chronic diseases
using Google trend data. Using advanced artificial intelli-
gence to diagnose diseases [40–42].

Thus, the objective of the present research was to build a
model that assists in predicting the influenza epidemic using
Google search queries. We integrated machine intelligence
with the existing time series model to enhance the prediction
of the influenza epidemic.

3. Materials and Methods

3.1. Data Sets

3.1.1. Epidemiological Surveillance Data. A weighted version
of CDC’s influenza-like illness (ILI) activity level data was
obtained from the Center for Disease Control and Pre-
vention, which routinely collected epidemiological data and
national statistics about influenza incidences on a weekly
basis. We collected the ILI data from January 4, 2009 (week
1) to December 27, 2015 (week 52), across a total period of
312 weeks. This period covered the data expressed during the
influenza seasons from the CDC in the USA. Data from the
CDC ILINet system were obtained from [43], which
provides weekly influenza surveillance information at the
national and regional levels of outpatient and viral illnesses.
We decided to use the CDC ILI because the CDC data is a
very strong data set. All reports about the CDC ILI are made
available [44].

3.1.2. Google Correlate. Google search engines have become
a significant part of everyone’s lifestyle. They have become
an indivisible clue for understating our lives. The Google
search engine helps us search for an individual or an area
and provides us with important information about events,
problems, solutions, and other stuff. Many search engines
are available, such as Google, Bing, AOL, Yahoo, and the
like. Since Google is the most famous search engine, we
searched for models using Google’s centre. Google has a
Google Trends centre that provides statistics on search
queries conducted around the globe, place, and moment.
Google has the facility of Google Trends, which provides the
statistics of the searches made in the world with respect to
the search query, location, and time. The Google Flu Trends
is a good example of this use to predict the influenza epi-
demic. Our ultimate objective is to construct a model similar
to the GFT system and other standard designs using open-
source information and enhanced methodology. Our ob-
jective in information collection is to discover open-source
search query information that looks like search queries used
for GFT. For each season, ILI information could be acquired
from the CDC as our basis. GFT system exploited 50 million
of the most popular database queries in the United States,
where a request was described as a full series of customer
words, to discover some queries mostly linked to CDC
information. Using a simpler technique, Google also con-
structed Google Correlate, which would provide informa-
tion that a customer could upload and the corresponding
daily time series of these queries, with the top 100 most
associated search queries at the domestic stage. Therefore, it
has used this tool to obtain an open-source dataset that
reasonably matches the query data used in the GFT model
that would not be released by Google. From January 4, 2009
(week 1) to December 27, 2015, we posted weighted CDC ILI
information to Google Correlate and achieved an output of
the 100 most important database queries. For each of these
Correlate queries, the time series was not the real amount,
but the quantity was subtracted by the median and split by
the standard deviation of the sample. The output time series
also ranged from January 4, 2004, through January 24, 2016.
The output time series also ranged from January 4, 2004,
through Jan 24, 2016. The Google Correlate has standardized
the search volume of each query to have means zero and
standard deviation one across time and contains data only
from 2004 to January 2016. We compared our model with
the original and revised (October 2014) Google Flu Trend
models. We observed that all the search terms obtained from
Google Correlate were related to influenza activity. The 10
search terms that have heights correlated are selected search
terms for predicting the influenza epidemic in this work.

To make Google Correlate data compatible with trend
data, the min-max normalisation method was used. The
3.2. Normalisation Method. Normalisation transformation of the appropriate time series typically helps to improve the prediction approaches widely used in industry and commerce.

3.3. Prediction Models. In this section, the proposed system is presented. Figure 1 shows the generic framework of the proposed system.

3.3.1. The Intelligent Time Series (INTS) Model. The INTS model explicitly predicts influenza outbreaks using Google search queries. Figure 2 illustrates how the INTS model can be a hybrid model with the existing time series prediction model and the k-means clustering algorithm. The prediction model was used to predict the influenza epidemic using Google search queries. Furthermore, the k-means clustering algorithm is employed to analyze the search pattern that has been obtained from the Google engine separately. The novelty of the INTS model lies in its integration of the results obtained from the WES time series prediction model along with the centroid obtained from k-means algorithms. The INTS model is a function of results obtained from the WES model and centroids of the k-means clustering algorithm.

EP, = \text{prediction function generated from the time series model and the centroid of clustering. The integrating model improved the prediction results. A comparative prediction result between the INTS model and existing times series models is presented. It is noted that the INTS model outperforms. The steps of the proposed INTS algorithm are discussed in the following subsections. The INTS algorithm is shown below: Let, S, be the sample of \text{i}th day, K be the number of clusters and \text{K}_i be the \text{i}th cluster, \text{C}_i is the centroid of \text{i}th cluster. Let \text{P}_i be the prediction for \text{i}th sample obtained by using WES model and \text{EP}, is an enhanced prediction for the\text{i}th sample obtained by using the proposed model (Algorithm 1).}

The components of the INTS proposed system are as follows:

(1) Weighted Exponential Smoothing (WES) Model. Exponential smoothing models are one of the most important prediction approaches widely used in industry and commerce.

\[
\ell_0 = \bar{y} = \frac{\sum_{t=1}^{n} y_t}{n},
\]

(2) K-Means Clustering Algorithm. Clustering time series is one of the most difficult clustering problems in information mining time series. Subsequence time series is used by a sliding window to remove the subsequence of items, which is segment clustering from a single long time series. Another type of clustering is time-point clustering, which is used to object point time points based on a combination of temporal proximity and the similarity of their respective values. This sort of time series clustering is similar to the segmentation of time series. However, time-point clustering is distinct from segmentation, owing to the fact that in time-point clustering of all items, it is not appropriate to add to the cluster because some of the items are deemed noisy. In the clustering of subsequent time series, it is important to observe how the technique can be used to categorize a vast quantity of time series data on how they can generate significant results. A most recent study has focused on subsequent time series clustering to improve time series models. Our goal was to focus on clustering in the centroid to improve the model of the WES time series. It is important to note that to improve the WES time series model, our technique was more viable. The strategy of k-means clustering is one of the easiest unsupervised teaching methods to address the well-known issues of clustering. K-means clustering processes are very simple and easy to classify in a certain amount of clusters (suppose k clusters) in a given information set.

\[
J = \sum_{i=1}^{c} \sum_{k=1}^{c_i} w_{ik}\|x^i - \mu_k\|^2,
\]
3.3.2. Support Vector Machine Regression (SVMR). The support vector machine regression (SVMR) model is an increasingly common version of the support vector machine used for problems with regression. Although the Support Vector Machine algorithm is common in classification issues, SVMR is trained to generate numerical values for regression. The general formulation of SVM and SVMR algorithms is very different. The basic idea in both SVMR and SVM is to map data set to a high-dimensional feature space through a mapping function called kernel function $\pi$ and SVM is to map data set and SVMR is to generate numerical values for the reality obtained target $y_i$ for the training data. The main principle is the same as the SVM classification, but we have a new function that can be minimized. In the $\varepsilon$-insensitive support vector regression, the main goal is to find a function $f(x)$ that has a deviation from the actually obtained target $y_i$ for all training data.

\[
f(x) = wx + b, \quad w \in X, b \in R.
\]

For this equation, we have to solve the following problem:

\[
\min \frac{1}{2}\|w\|^2.
\]

Subject to

\[
y_i - wx_i - b \leq \varepsilon,
\]
\[
wx_i + b - y_i \leq \varepsilon.
\]

If the problems are not feasible, we need to introduce the slack variables $\xi_i, \xi_i^*$ as it is called soft margin:

\[
\min \frac{1}{2}\|w\|^2 + C \sum_{i=1}^{l}(\xi_i + \xi_i^*).
\]

Subject to

\[
y_i - wx_i - b \leq \varepsilon + \xi_i,
\]
\[
wx_i + b - y_i \leq \varepsilon + \xi_i^*, \quad \xi_i, \xi_i^* \geq 0, C > 0,
\]

For determination, the trade-off between the flatness of $f(x)$ by using $C$, the amount up for deviations is larger than $\varepsilon$-tolerance. This case is called $\varepsilon$-insensitive loss function $|\xi|_\varepsilon$ and this can be as follows.

Figure 3 displays the hyperplane of the SVM algorithm when the hyperplane separates the data into classification and regression purposes. The SVM algorithm is used for classification data; it is a very powerful machine learning algorithm for classification, and the SVM algorithm has the ability to solve the regression problem, as shown in Figure 3. Figure 4 displays the process of the SVMR model to predict influenza outbreaks using Google search queries.

3.3.3. Artificial Neural Network Using Particle Swarm Optimisation (ANPSO). Particle swarm optimisation was developed for a global optimisation system, PSO, which is a group based on a stochastic optimisation method for nonstop nonlinear capacities. In correlation with other metaheuristics, PSO has acquired prevalence and is indicated plainly to be successful, and it focused on enhancement calculation. Every part of the PSO technique has been known as particle flies around the multidimensional search space with a velocity, which is constantly raised to date by the particle’s own particular experience and the experience of the particle’s neighbours or the experience of the whole swarm. It implies two errors of the PSO algorithm are created: PSO with a neighbourhood in the global and PSO method with neighbourhood overall worldwide. As indicated by the global surroundings, every particle moves towards its best past position and towards the best particle in the whole swarm, called gbest demonstrate [47, 48]. Furthermore, as indicated by the local disparity called lbest, every particle moves towards its best past position and towards the best particle in its limited neighbourhood. While PSO has a memory of the past, the learning of a good solution is kept by all particles. Particles cooperate in a helpful way to share data in the swarm. The particle swarm optimisation (PSO) algorithm is based on a velocity update and position update. Velocity updates the following equation:

\[
v_i(t+1) = wv_i(t) + c_1r_1(p_i(t) - x_i(t)) + c_2r_2(p_g(t) - x_i(t)),
\]

where random inertia weight was calculated according to the equation as follows:

\[
w = 0.5 + \frac{\text{rand}()}{2.0}.
\]

Artificial neural network (ANN) is a type of computational model that is regularly utilized in the fields of machine learning, software engineering, and other research disciplines. This computational model is composed to mirror the immense system of neurons in a brain. It is commonly

| Table 1: Most significant 10 Google search terms. |
|-----------------------------------------------|
| Flu duration |
| Thermoscan |
| Fever flu |
| Influenza type a |
| Flu fever |
| Oscillococcinum |
| Braunthermoscan |
| Cold versus |
| Flu treating flu |
| Flu headache |

**Subject to**

\[
y_i - wx_i - b \leq \varepsilon + \xi_i,
\]
\[
wx_i + b - y_i \leq \varepsilon + \xi_i^*, \quad \xi_i, \xi_i^* \geq 0, C > 0.
\]
utilized for issues that are hard to be unequivocally cus-
tomised in view of its capacity to gain from cases. The type of
ANN utilized this exploration, which is completely associ-
ated with feedforward that organizes where each input is
associated equitably with all the hidden neurons. For sim-
plicity and preparation speed purposes, only a single hidden
layer was utilized in the system. PSO is a global search and
population-based algorithm used to train neural networks,
identify neural network architectures, adjust network
learning parameters, and optimize network weights. PSO
avoids trapping at a minimum local level because it is not
based on information about gradients [47]. PSO function in
ANN is to obtain the best set of weights (particle position)
where several particles try to move to obtain the best so-

tion. The search space dimension comprises cumulative
weights and prejudices. By following the personal best so-
lution of each particle and the best global amount of the
entire swarm, the algorithm finishes the optimisation. A
population-based algorithm’s success or failure depends on
its ability to trade efficiently between discovery and

| Table 2: Google search queries obtained from Google Correlate. |
|---------------------------------------------------------------|
| Flu duration | Symptoms flu |
| Thermoscan | Flu contagious period |
| Fever flu | Viral pneumonia |
| Influenza type a | Flu complications |
| Flu fever | Flu relapse |
| Oscillococcinum | Treat flu symptoms |
| Braunthermoscan | Flu in babies |
| Cold versus flu | Flu or cold |
| Treating flu | Flu quiz |
| Flu headache | What is tamiflu |
| Flu and fever | Duration of flu |
| Cold and flu symptoms | Flu germs |
| Tamiflu and breastfeeding | Human temperature |
| Flu in kids | Cold flu |
| Flu lasts | Tamiflu liquid |
| Tylenol flu | Treating flu symptoms |
| is tamiflu safe | Flu remedy |
| Flu symptoms last | Contagious flu |
| Anasbarbariae | Ear thermometer |
| Flu how long | Flu type a |
| Flu recovery | Cold or flu |
| Flu versus cold | Flu nausea |
| Side effects of tamiflu | Common flu symptoms |
| Type a flu | Common cold symptoms |
| Flu how long does it last | Influenza a |
| Low body temperature | Flu sweating |
| Treatment of flu | Oscillo |
| Flu dizziness | Length of flu |
| Flu recovery time | Flu in infants |
| Cold vs. flu | CDC Tamiflu |
| Flu length | Dangerous fever |
| Tamiflu side effects | What is influenza |
| Flu vomiting | Tamiflu suspension |
| Tamiflu in pregnancy | When to take Tamiflu |
| Flu without fever | Should I take Tamiflu |
| Flu stomach | Rapid flu test |
| Low body | Mild flu |
| Flu cough | Flu in adults |
| Tamiflu and alcohol | Fever temperature |
| Flu a and b | Tamiflu prophylaxis |
| Flu chest pain | Flu fever duration |
| Tamiflu dose | is it a cold or the flu |
| Flu contagious | Homeopathic flu |
| What is influenza a | Flu and rash |
| Treating the flu | Flu vs. cold |
| Flu how long contagious | Viral flu |
| Taking temperature | Tamiflu drug |
| Flu in toddlers | Fever reducers |
| Cough flu | Treat flu |
| Flu back pain | How to get over the flu |
extraction. An inappropriate balance between exploration and extraction can result in a poor method of optimisation, which may suffer from premature convergence, local optimum trapping, and stagnation. Figure 5 shows the flow process of the ANNPSO model for predicting the influenza epidemic using Google search queries.

3.4. Performance Metrics. Four error indicators were used to evaluate the prediction model. The mean square error, root mean square error, and mean absolute error were used as performance indices. Those methods of standard indicators are defined as follows:

\[
\text{MSE} = \frac{1}{N} \sum_{k=1}^{n} (x_t - \bar{x}_t)^2, \quad (12)
\]

where \(x_t\) is observed responses, \(\bar{x}_t\) are estimated responses, and \(N\) is the total number of observations.

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{k=1}^{n} (x_t - \bar{x}_t)^2}, \quad (13)
\]

where \(x_t\) is observed responses, \(\bar{x}_t\) are estimated responses, and \(N\) is the total number of observations.

\[
\text{MAE} = |x_t - \bar{x}_t|, \quad (14)
\]

where \(x_t\) and \(\bar{x}_t\) are the estimated and observed responses, respectively.

4. Results Analysis

Our analyses used the data from January 4, 2009 (week 1) to December 27, 2015 (week 52) across a total period of 312 weeks, covering 7 years of the CDC data. The CDC data are uploaded to Google Correlate, obtaining 100 search query terms that are related to the influenza epidemic. In total, 10 search terms were analyzed in this study. The 10 search queries with the highest correlation have been selected. The min-max method was used for normalisation purposes, and three experiments were conducted to obtain the prediction result. These three experiments are presented in the following section.

4.1. Results Analysis of the INTS Model. The Weighted Exponential Smoothing algorithm was applied to search terms obtained from Google correlate. The weighted exponential smoothing model depends on the \(\alpha\) smoothing constant; it was then tested with values from 0.1 to 0.9. The MSE performance measure was scrutinized through the use of these parameters. The \(\alpha = 0.9\) parameter was selected as a
smoothing constant. It was observed that $\alpha = 0.9$ was appropriate for data prediction. Moreover, $\alpha = 0.9$ is given fewer errors as compared to other parameters. To enhance the prediction of the conventional weighted exponential smoothing model, the $k$-means clustering algorithm is used. The first step was to determine the number of clusters for $k$-means clustering. It was made up of eight clusters. After determining the existence of one cluster that had fewer objects, it was decided to reduce the cluster numbers until all clusters with more objects were obtained. Lastly, we determined that the five clusters were appropriate.

Then, it should be considered for centroids of cluster numbers. Each assigned object belongs to the specific cluster by centroids. The centroids were integrated with the results that have been achieved from the existing WES algorithm. The predictive capabilities of our intelligent model were compared with the existing GFT, ARGO, GFT + AR, AR (3), and naive models. Therefore, the comparison is presented by employing CDC real data. MSE, RMSE, and MAE were used to evaluate and estimate the performance of the INTS proposed model in comparison with the existing prediction models. The obtained results showed significant advantages for our proposed model. It was obvious that the INTS model is the most effective and robust predictor that can be used to enhance the prediction of the influenza epidemic using search terms. Table 3 summarizes the results obtained from our INTS model. The INTS model had shown the best performance in relation to MSE, INTS = 0.0014, RMSE = 0.0369, and MAE = 0.0185. We noticed that the INTS model outperformed all existing models. We used correlated increments between the prediction and original CDC data. We observed that the INTS model had more correlation when compared to other conventional models such as ARGO and GFT. The increment correlate obtained from the INTS model was 0.931. These findings indicate that the INTS model improved influenza epidemic prediction using search queries. Figure 6 illustrates the performance prediction of the intelligent time series model. Figure 7 shows the performance of the regression plot of the INT model.

### 4.2 Results Analysis of the ANNPSO Model

ANNPSO intelligent models have been implemented to predict the influenza epidemic using Google search terms. The Min-Max method is presented to scale the data to enhance the prediction models. Adapting the ANNPSO model was applied to develop a smart healthcare system. Since the weights of the ANN need to be optimized, the position of the particles in the PSO algorithm needs to be tracked. The issue space includes combinations of all weight values of the ANN algorithm. This search space consists of $n$-dimensions, where $n$ is the total number of weights to optimize. Each particle has an $n$-dimensional location vector and speed vector. The particle swarm optimisation is flying around this search space and creating the optimum weight set. The weights are allocated to the ANN while assessing the fitness of a particle in the PSO, and its predictive precision is discovered. This offers the particle’s fitness. If fitness is the best so far for the particle, it will be taken as its personal best, and if it is the best so far for the swarm, it is considered the best global. The adapting model helps to improve prediction results. These particle swarms were used to improve the weight of the ANN approach. 25 particles were considered for 200 iterations.
Table 3 summarizes the prediction results of ANNNPSO to predict influenza epidemics. It is noted that the adapting model obtained satisfying results. The prediction results were $\text{MSE} = 0.0024$ and $\text{RMSE} = 0.493$, $\text{MAE} = 0.25$, and $R = 0.94\%$. The obtained results have proved that Google search queries have the strongest relationship with clinical data. Figures 8 and 9 display the performance of the ANNNPSO model.

4.3. Results Analysis of the SVMR Model. Table 3 demonstrates the prediction results obtained from adapting the SVMR model. It is reported that the proposed model has performed good results. The support vector machine algorithm was applied to predict influenza, and we used the RBF kernel. The RBF kernel function has robust efficiency compared with other SVM functions. The kernel parameter values $C, \gamma, \varepsilon$ were tested to attain the best performance by changing parameter values. The optimum parameter values were selected according to the lowest obtained errors. The prediction results show that there is a relationship between clinical data and web search terms. According to the MSE, RMSE, MAE, and $R = 0.99$ obtained results of 0.136, 0.369, and 3.888, it is indicated that clinical data has more impact on the web search. Thus, Figures 10 and 11 exhibit the estimation performance of the SVMR model for predicting the influenza outbreak.

5. Discussion

In the present research paper, some significant implications have been presented for estimating and predicting the influenza epidemic at the local and national levels of USA.
influenza data. In addition, early and precise detection of influenza outbreaks can assist in advising attempts to reduce the spread and effects of influenza outbreaks. The government can educate vaccination campaigns against influenza outbreaks at the local and national levels. Having a precise scheme for monitoring influenza forecasts is especially useful for preventing and controlling the spread of influenza to other areas of the nation. Despite the fact that there is a

Table 3: Results of prediction models for predicting influenza epidemics using Google search queries.

| Models   | MSE   | RMSE  | MAE   | Correlation |
|----------|-------|-------|-------|-------------|
| INTS     | 0.0013| 0.0369| 0.0185| 0.97        |
| ANNPSO   | 0.0024| 0.0493| 0.259 | 0.94        |
| SVMR     | 0.136 | 0.369 | 0.388 | 0.99        |
trend towards modernizing surveillance of the influenza epidemic, the current standard models for influenza surveillance have documented shortcomings, including low sensitivity and less accuracy. Consequently, the need to take steps to improve influenza surveillance has been well acknowledged. Three adapting algorithms, namely, our INTS model, ANNPSO, and SVMR models, were implemented to predict the influenza epidemic. Hence, in the present study, we implemented an INTS model that can help to enhance the existing WES model and the time series model for predicting the influenza epidemic. Our idea focuses on the centroids of clustering to improve the existing WES model and the time series model for predicting the influenza epidemic. The INTS model, assisted by a conventional time series prediction model and an appropriate machine intelligence approach, was used to predict influenza outbreaks using the Google search pattern. It is observed that our model is more feasible for improving the time series model to predict the influenza epidemic. Figure 8 displays the correlation of INTS, and it is observed that the percentage of correlation is $R = 0.97$. The prediction results of this research demonstrate that, in general, models are built by Google search queries for estimating and predicting influenza outbreaks.

Furthermore, we have applied the adapting ANNPSO and SVMR models, which have performed better; it is noted that prediction errors are the lowest. These adapting models are compared with alternative models; they perform better for predicting influenza. These models were able to satisfactorily estimate true influenza outbreaks according to the official influenza case counts reported by the CDC for either a whole period or a seasoning period. The INTS model was compared with different existing models. The existing
prediction models with different input data sets have used the pattern of the whole period and seasonal period. But, the INST model is used for one input data, with a whole dataset. The results obtained from the intelligent model were compared with different existing models using different input data sets throughout the period and the season. We observed that the INTS model outperformed all other alternative models of different input data with respect to MSE, RMSE, MAE, and increment correlate. Table 4 shows the prediction results of adapting the models against the existing.

**Figure 8:** Performance of the ANNPSO model. (a) Train data. (b) MSE = 0.0024304, RMSE = 0.049299, and MAE = 0.2594. (c) Error St. D. = 0.049355.

**Figure 9:** Performance regression plot of the ANNPSO model.
The results of the INTS model are 0.0013, 0.0369, and 0.0185, according to MSE, RMS, and MAE. These results have been compared with other alternative strangest models, which are ARGO = 0.3696, GFT = 4.9106, AR model = 0.915, naive model = 0.1211, and proposed adapting models ANNPS = 0.0024 and SVMR = 0.136 with respective to MSE metric. According to the RMSE evaluation metric, the INTS model = 0.0369, and other alternative

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**Figure 10**: Performance of the SVMR model. (a) Train data. (b) MSE = 0.11444, RMSE = 0.33829, and MAE = 3.8887. (c) Error St. D. = 0.081002.

**Figure 11**: Performance regression plot of the SVMR model.
6. Conclusions

Web activities are an important source for obtaining health information. Consequently, web searches provide vital information regarding numerous infectious disease activities. For example, an influenza epidemic can occur when an infectious disease quickly spreads to many people. As a further instance, the web can efficiently perform a thorough examination of the relationship between search queries of influenza and actual influenza occurrence. Three adapting prediction models, namely INTS, ANNPSO, and SVMR, were presented to improve the prediction of the influenza epidemic by using Google search queries. The methodology of these proposed models outperformed other existing models and provided higher accuracy and robustness in predicting influenza. The former models were originally implemented to predict influenza using Google search terms. However, the novelty of the proposed research is the development of the INTS model, which is a new model for predicting the influenza epidemic. The prediction results demonstrate that the proposed INTS model can be effectively employed to predict influenza outbreaks using Google search queries. A comparative prediction result between GFT, AGRO models, and the present SVMR and ANNPSO models is presented. It has been observed that the results of the alternative model are 0.0013, 0.0369, 0.0185, and 0.97, in accordance with MSE, RMSE, MAE, and correlate of increment performance measures. Respectively, it is also observed that the INTS model is more satisfying in comparison to the existing models like ARGO and GFT.

Data Availability

The researchers can collect the data from https://gis.cdc.gov/grasp/fluview/FluView8.html and https://www.google.com/trends.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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