Multi-Step Forecasting Method For Influenza Pandemic Using Long Short-Term Memory Model To Improve Public Health Conditions

Dr. Rajesh Keshavrao Deshmukh[1], Mohit Shrivastav[2]

[1]*Assistant Professor, Department of CS & IT, Kalinga University, Raipur, India.*

[2]*Research Scholar, Department of CS & IT, Kalinga University, Raipur, India.*

KEYWORDS

Influenza, Long Short-Term Memory, Public Health, Prediction.

ABSTRACT

The flu spread is a major global public health problem that gets attention around the world because it can cause serious illness, cost a lot of money, and kill a lot of people every year. To avoid influenza-like disease (ILD) and run healthcare systems well, predicting when an influenza outbreak will happen is essential. Researchers have used Machine Learning (ML) techniques but have yet to find the best ways to see complicated, non-linear trends in sequential data about flu outbreaks. A Long Short-Term Memory (LSTM) and a Genetic Algorithm (GA) are used together in this study to show a new way to predict multi-step influenza breakouts. Every week, the study gathers information on ILD, which covers flu and other illnesses with signs similar to the flu. When measuring performance during busy times, the suggested model does much better than other advanced Machine Learning (ML) methods and Fully Connected Neural Networks (F-CNN).

1. Introduction

Influenza, or "flu," affects people's health every year worldwide [1]. The flu outbreak is thought to have caused significant illness in about 3–5 million people yearly and killed 250,000–500,000. Each year, the flu outbreak in the US claimed 610k life-years, hospitalized 3.2 million days, and admitted 32.6 million people to outpatient facilities. The annual flu outbreak resulted in a financial burden of $88.3 billion, as calculated using estimated statistical life estimates. Regarding economic impact, the flu is considered one of the most expensive global epidemics.

The influenza vaccine is highly effective in minimizing the likelihood of contracting and transmitting the flu virus to others [2]. In the 2017-2019 flu season, the flu vaccine successfully averted around 6.2 million cases of the disease, 3.1 million healthcare visits, 72k hospitalizations, and 3k deaths caused by pneumonia and influenza [4]. Due to the flu virus's significant evolution rates and continual genetic re-assortment, the process of making flu vaccines is complex and challenging each year. Every February, the World Health Organization (WHO) evaluates various flu viruses expected to become prevalent over the upcoming winter [3]. Vaccine producers manufacture flu vaccinations within a highly restricted timeframe. Allocating hospital rooms to patients with flu is complex because of the restricted bed capacity, time-sensitive arrival of bed requests, and specific treatment needs of flu patients [10]. The timing, seriousness, and length of flu seasons differ from one season to another.

To enhance the preparedness of hospitals and drug companies for an annual flu epidemic, developing a precise model capable of performing Multi-Step-Ahead Time-Series Forecasting (MSA-TSF) for flu epidemics is essential [15]. MSA-TSF, or Multi-Step Forecasting (MSF), is an analytical activity that predicts potential outcomes by analyzing past measured values [5]. Previous studies need to include more research on MSF for flu outbreaks. The explanation could be that MSF often leads to low accuracy due to specific insurmountable issues, such as accumulating errors. While the single-step forecast has the advantage of avoiding low accuracy, it will prevent us from gaining insight into the pattern and variability that occur over the following month.

Background and Related Works

Various researchers, including Wang et al., have tried to improve the precision of predicting influenza epidemics [6]. This is crucial since early identification and real-time surveillance of outbreaks are highly significant. The current methodologies for predicting influenza dynamics can be separated into two main domains: conventional approaches and Machine Learning (ML) techniques.

Tsan et al. reviewed the research on Long Short-Term Memory (LSTM) and its different types [16]. The LSTM networks were created by Ding et al. to predict stock market prices using a lot of sequential information [7][8]. Zheng et al. created a one-of-a-kind model that combines LSTM and attentional processes to find important factors for predicting traffic flow [9]. The LSTM model was developed by Zhu et al. to study how environmental factors affect predicting flu [17]. A modified LSTM model was used by Amendolara et al. to predict flu breakouts several steps ahead of time [11]. Zhang et al. used an LSTM to guess the ILD rate based on information from the surroundings, Google Trends, and how the flu spreads [12].

Researchers used Deep Neural Network (DNN) techniques to find the hyperparameters. They did this by hand, trying different search methods like random and grid-based searches. A Genetic Algorithm (GA), an Artificial Bee Colony (ABC), and Particle Swarming Optimization (PSO) are some of the metaheuristic-based methods that academics have used to solve this problem. A time series framework for petroleum production was made by Kumar et al., who combined LSTM and GA [13]. They used GA to make the LSTM model's factors work better. An LSTM was built by Son et al. to predict energy load [14]. Using a GA, they told the network to choose the settings that would work best for the framework. This study differs from others on LSTM structure and variables because it carefully looks at all of them, such as the windows, LSTM levels, links inside each LSTM level, and intervals.

Proposed LSTM and GA-based Public Health Detection Model

The MSA-TSF problem aims to guess what a target variable will be worth by looking at a series of readings from the past. This study looks at the raw data, a one-variable time series that shows how many ILDs happened at each step, with a weekly frequency. The suggested model handles a single-variable time series data set from a range. This information includes a weekly total of ILD cases and is used to create a prediction about what will happen. The Neural Network (NN) determines the best method settings that lower costs.

Deep NN (DNN) designs are better than other ways of solving problems that aren't fixed or complicated. It is crucial to ascertain the optimal variables and design of DNN regarding overfitting and computing efficiency. This study focuses on developing a proposed method that combines LSTM and GA to enhance the precision of predicting influenza outbreaks with several steps. The GA, a process that combines meta-heuristic and stochastic optimizing techniques, has proven to be highly efficient in obtaining either near-optimal or ideal solutions. It aims to get the optimal solution by selecting a set of choice variables that maximize a fitness function among a wide range of feasible solutions. This work considers choice factors: the amount of LSTM levels, the number of units, the number of phases, and the windowing dimension. Initially, the method commences by randomly generating a starting group of numerous elements. The fitness rating of every person in the group is computed. GA employs many primary stages to create new offspring from the existing population: selections, crossovers, and mutations. The selecting stage focuses on safeguarding elements with superior fitness standards when removing those with more severe fitness levels. During the crossover stage, specific genes (variables) from two chosen individuals are exchanged to generate additional people. The primary objective of the mutation stage is to introduce random changes to the characteristics of individuals, promote diversity within the population, and address the problem of being stuck in a suboptimal solution. Figure 1 illustrates the architecture of the proposed forecasting algorithm.

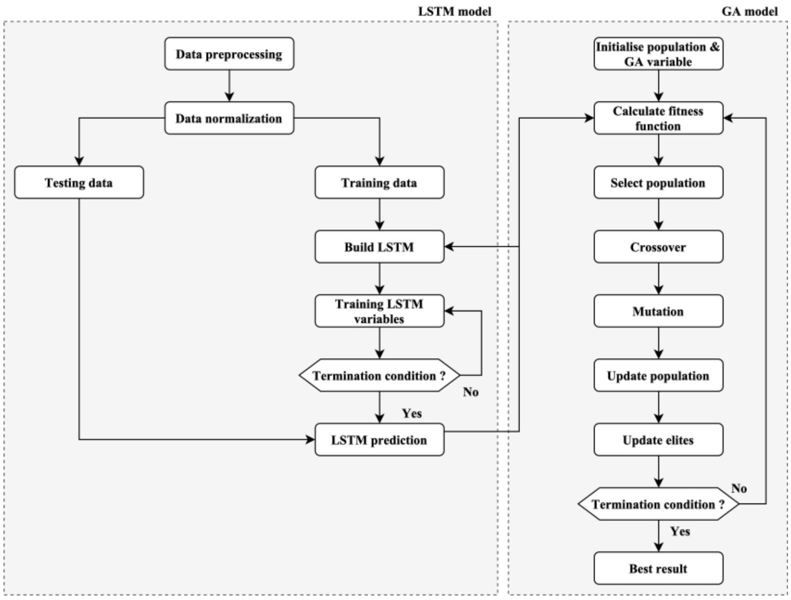

Figure 1. The suggested forecasting model for public health

The proposed model utilizes the mistake as the fitness parameter for the GA in estimating influenza outbreaks. The populations reflecting potential solutions get started with randomly assigned values. The framework employs the NSGA-II method for selecting and the two-dimensional method for the cross-over phase. The GA mutating operation was executed by choosing random values within the specified range. The choice variables of the issue are represented as integers in this research. The solution with the minimum RMSE is considered ideal.

Simulation Analysis and Outcomes

The efficacy of the proposed approach, which is suggested for MSA-TSF, is contrasted to that of the Random Forests (RF), Support Vector Machines (SVM), and Fully-Connected Neuronal Networking (F-CNN) models. GA is employed to identify the ideal or nearly optimal variables for the proposed model and F-CNN. This study examined the time-based variability of the observed and predicted scores of multiple methods (Proposed, F-CNN, and SVM) for predicting at a time horizon of t +1. Figure 2 illustrates the comprehensive outcomes of the fundamental, estimated, and discrepancy values (the disparity between actual and estimated). Every model correlates with the observed results and the projected values. The proposed model exhibits superior efficiency in capturing temporal variation at peak times. The SVM model's predictions displayed a tendency for underestimating higher values. The predictive capabilities of the proposed models and F-CNN scenarios are more practical and precise than those of the SVM model, which relies on ML.

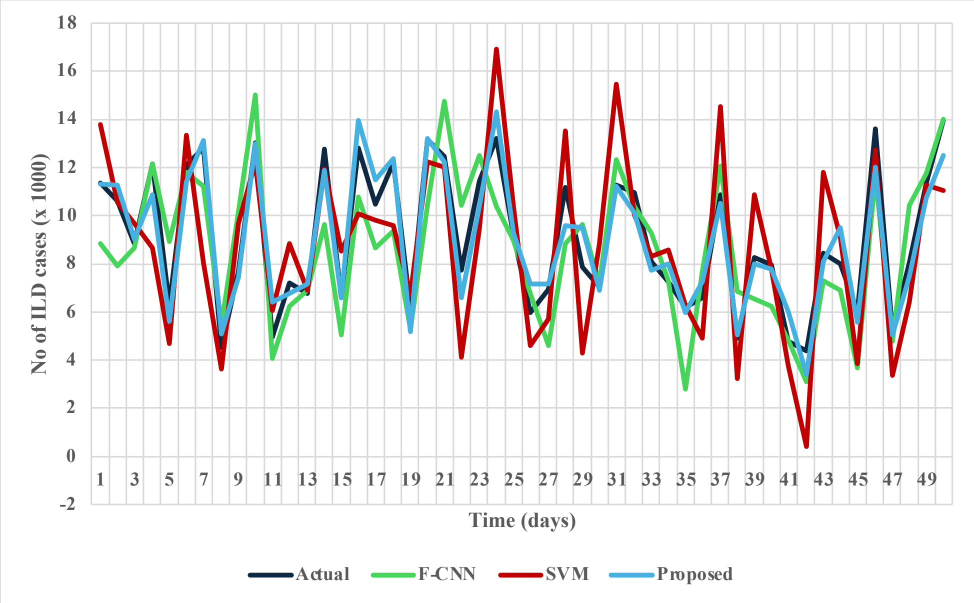

Figure 2. ILD prediction results

Table 1 demonstrates the efficacy of the techniques during the summer and winter months when the influenza outbreaks reached their highest point. During periods of high demand, the analytical outcomes indicated that the suggested approach surpassed the other techniques. The ML-based SVM and RF methods exhibit inferior performance compared to the different methods. During periods of low demand, it has been determined that the ML-based SVM and RF methods outperform other approaches in terms of Mean Absolute Error (MAE), RMSE, R-squared (R2), and Standard Error (SE). During off-peak hours, the efficacy of the proposed model and F-CNN approaches is reduced compared to peak times. The maximum times have elevated scores of temporal leftovers and encompass additional intricate trends than the non-maximum times.

Table 1. Prediction results for summer and winter months

Time	Method	MAE (%)	RMSE (%)	R2 (%)	SE (%)
Winter	RF	3.24	8.43	64.21	2.32
	SVM	4.64	9.56	59.45	4.23
	F-CNN	6.42	6.94	48.64	2.53
	Proposed	2.13	3.24	12.49	0.53
Summer	RF	4.23	8.64	68.42	3.12
	SVM	5.23	9.74	61.35	5.32
	F-CNN	7.12	6.74	49.62	4.73
	Proposed	2.16	3.12	10.49	0.62

The suggested method often aims to detect intricate and time-space patterns during high-traffic periods to minimize forecast inaccuracies on the test information. Considering all these findings, the proposed technique has demonstrated satisfactory results for predicting MSA-TSF outbreaks with maximum times, known as outbreak times, related to alternative methods.

2. Conclusion and future scope

This study focuses on a hybrid model that utilizes ML to estimate the activity of influenza outbreaks more accurately. The objective of this integrated approach, combining LSTM and GA, is to derive high-quality characteristics that accurately capture the complex and non-linear characteristics of MSA-TSF. It tries to establish the ideal variables and structure of the neural network. The proposed model can forecast present and future influenza activities with greater accuracy and efficiency. The suggested model's resilience and utility are assessed by contrasting it to the statistical model, an F-CNN, and ML methods such as RF and SVM. The optimal hyperparameter scores for RF and SVM were determined utilizing 5-fold cross-verification with the grid search method. The hyperparameter variables of the F-CNN are tuned using a GA.

The disparities between the measured and forecasted scores in the proposed model are comparatively fewer than in the other benchmarking scenarios, particularly for higher values. Regarding the findings of the prediction of the MSA-TSF, the errors in all models rise as the projected timeframes extend. Future research will explore the impact of MSA-TSF information on the accuracy of influenza prediction utilizing LSTM. It will prioritize identifying the most influential variables and structure of the LSTM.

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