Simulation of influenza dynamics with LSTM deep learning model *

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Abstract

Influenza remains a significant public health concern worldwide, especially in regions affected by conflict, where healthcare systems are compromised. This study aims to develop a forecasting model for influenza in the war-affected Kharkiv Oblast of Ukraine, leveraging a Long Short-Term Memory (LSTM) deep learning approach. The LSTM model was trained using monthly influenza incidence data from January 2013 to April 2024 to predict short-term outbreak dynamics. Hyperparameters such as LSTM units, dropout rates, and optimizers were fine-tuned to optimize the model. The model's performance was evaluated using mean squared error (MSE) and mean absolute percentage error (MAPE), achieving a best MSE of 0.0255 and a MAPE of 6.3976. The study contributes both scientifically and practically by applying machine learning techniques to influenza forecasting in a conflict zone, a context not extensively studied before. The LSTM model demonstrated robustness in handling incomplete and irregular data, offering reliable short-term forecasts critical for public health interventions in regions with disrupted healthcare systems. The findings of this study provide a framework that can be applied to other conflict-affected regions facing similar public health challenges.

Keywords

Epidemic model, LSTM, deep learning, infectious disease simulation

1. Introduction

Influenza is a widespread viral infection that affects the upper respiratory system, caused by the influenza virus. It is highly contagious and is transmitted through respiratory droplets when infected individuals cough, sneeze, or talk [1]. The symptoms of influenza include fever, cough, sore throat, body aches, headaches, fatigue, and sometimes gastrointestinal issues such as nausea and diarrhea [2]. While influenza typically results in mild to moderate symptoms, it can become severe and even fatal in high-risk populations, such as young children, the elderly, pregnant women, and individuals with pre-existing medical conditions [3]. The seasonal nature of influenza, with peaks typically occurring during the colder months and its propensity for antigenic variation through mutation and reassortment, requires ongoing public health surveillance and interventions, including annual vaccination campaigns to match circulating strains and reduce the impact of outbreaks [4].

On a global scale, influenza remains a persistent public health threat, causing significant morbidity and mortality each year. The World Health Organization (WHO) estimates that seasonal influenza epidemics result in 3 to 5 million cases of severe illness and up to 650,000 respiratory deaths worldwide annually [5]. These figures underline the substantial burden influenza places on healthcare systems, especially during peak flu season when hospitals and clinics often face surges in admissions and demand for medical resources. Influenza is a dynamic virus that can mutate rapidly, requiring health authorities to adjust vaccine formulations annually to keep pace with evolving strains. Despite

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the availability of vaccines, the flu continues to spread due to varying vaccine coverage rates, vaccine hesitancy, and the potential mismatch between the vaccine and circulating virus strains [6]. International collaboration through institutions such as WHO and the Global Influenza Surveillance and Response System is vital in monitoring flu trends, updating vaccines, and coordinating response efforts to mitigate the virus's impact [7].

In the context of Ukraine, influenza has become an increasingly pressing issue due to the Russian full-scale invasion that began in 2022. The invasion has severely disrupted Ukraine’s healthcare system, affecting the delivery of medical services, including routine vaccinations against influenza [8]. With millions of people displaced both within and outside the country, overcrowded living conditions in refugee camps, shelters, and temporary housing have increased the transmission of infectious diseases, including influenza [9]. Furthermore, the disruption of healthcare infrastructure has limited access to essential medicines and medical care, particularly in conflict zones. Vulnerable groups, such as the elderly and children, face heightened risks in this precarious situation, as overcrowding and insufficient medical attention create optimal conditions for the virus to spread rapidly [10]. The situation is further compounded by psychological stress and poor nutrition, which can weaken immune systems and increase susceptibility to infections [11]. Effective influenza management in Ukraine under these conditions requires innovative public health approaches, including disease modeling and simulation, to predict outbreaks and allocate resources where they are most needed.

The field of data-driven healthcare, specifically public health informatics, has seen rapid advancement in recent years, driven by the increasing availability of healthcare data and advances in machine learning and artificial intelligence (AI) [12]. Public health informatics focuses on collecting, managing, and analysing health data to inform decision-making and improve health outcomes. In this context, machine learning models are increasingly critical in predicting disease outbreaks, monitoring health trends, and guiding public health responses [13]. By leveraging large datasets that include historical health records, vaccination coverage, population density, and environmental factors, machine learning models can accurately uncover hidden patterns and predict disease spread [14]. These models have been particularly useful in influenza research, where predictive modelling helps public health officials forecast flu seasons, identify at-risk populations, and develop vaccine distribution and outbreak prevention strategies [15]. Furthermore, machine learning models enable real-time analysis, allowing health authorities to quickly adjust interventions based on evolving data, which is crucial in managing fast-spreading infectious diseases like influenza [16].

Simulating the spread of infectious diseases, such as influenza, is essential for understanding transmission dynamics and planning effective interventions. Infectious disease simulation models allow researchers to test various scenarios and predict how diseases might spread under different conditions, such as changes in vaccination rates, population movements, or healthcare interventions [17]. These models are important tools in epidemiology, as they can provide insights into how a virus like influenza spreads through populations over time. Models can be constructed to account for various variables, including population density, age distribution, social behaviours, contact patterns, vaccination coverage, and the effects of public health interventions such as quarantines or school closures [18]. Among these simulation models, Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), have shown significant promise in predicting the spread of diseases due to their ability to capture temporal dependencies in sequential data [19]. LSTM networks are particularly useful for modelling time-series data, which is crucial in understanding how diseases progress over time and space. By training LSTM models on historical influenza data, researchers can simulate the spread of the virus and forecast future outbreaks. These simulations are vital for public health officials to plan interventions, allocate resources, and make data-driven decisions responding to potential flu outbreaks. In complex situations, such as Ukraine's ongoing conflict, these simulations can offer valuable insights into how the influenza virus might spread among displaced populations and help health authorities prioritize vaccination and other public health measures to control the disease's impact.

The aim of the study is to develop the forecasting model of influenza in war-affected Kharkiv Oblast of Ukraine based on LSTM deep learning approach.

Current research is a part of the comprehensive information system for assessing the impact of emergencies on the spread of infectious diseases described in [20].

2. Current Research Analysis

Machine learning methods have become increasingly valuable tools for simulating and predicting the spread of influenza due to their ability to process large datasets and identify complex patterns in disease transmission. Various models, such as decision trees, support vector machines (SVMs), and deep learning algorithms, have been applied to influenza forecasting with promising results. These models can analyze multiple factors that influence the spread of the virus, including environmental conditions, population mobility, and vaccination coverage. Among these approaches, recurrent RNNs, particularly LSTM models, have gained attention for their effectiveness in capturing temporal dependencies in sequential data, such as disease progression over time. Machine learning models can offer accurate predictions critical for public health planning and timely interventions by utilizing historical data on influenza outbreaks.

The paper [21] presents a framework for predicting influenza-like illness (ILI) trends using multiple machine learning models. The study developed and validated four models: ARIMA, random forest, support vector regression, and extreme gradient boosting, and then combined their outputs using an ensemble method called stacking. The models were trained on historical influenza data from 2008 to 2014 and tested on data from 2015 to 2017. The ensemble approach provided accurate real-time predictions of ILI visits up to 4 weeks in advance, improving public health preparedness. A notable limitation is the model's decreased accuracy over longer time horizons, and while it performs well for short-term forecasting, it struggles with predicting longer-term trends.

The study [22] explores how human mobility data can be used to predict the spread of influenza. By leveraging anonymized mobility data from smartphones, the authors developed a metapopulation model to forecast influenza outbreaks in the U.S. and Australia. Their approach showed that mobility data enhances forecasting performance, especially compared to traditional models based on static data like commuter surveys. The study demonstrates the utility of real-time mobility data for predicting disease transmission across geographic boundaries. However, the work has some limitations. The accuracy of predictions depends heavily on the quality and timeliness of mobility data, and the model struggles to account for variations in population dwell times and transient populations, such as tourists.

Research [23] explores the effectiveness of using ensemble forecasting to predict seasonal influenza outbreaks. The authors combined 21 forecasting models using a stacking ensemble technique and tested them in real-time during the 2017-2018 influenza season. The multi-model ensemble outperformed individual models and a simple averaging approach by incorporating past performance to weight the models. This approach was particularly successful during one of the most severe flu seasons in recent history, improving the accuracy and reducing variability across regions. A limitation of the study is that the performance of the ensemble models relied heavily on historical data, making it less adaptable for novel, unexpected scenarios, such as pandemics without historical precedence.

The paper [24] evaluates using an LSTM deep learning model for predicting short-term ILI trends. The model was trained using historical influenza, climate, and population data from the Centers for Disease Control and Prevention (CDC), the National Center for Environmental Information (NCEI), and the U.S. Census Bureau. Results indicated that temperature and precipitation were the most significant predictors of ILI rates, with the LSTM model outperforming traditional regression models like random forests and ARIMA. The LSTM model demonstrated a notable reduction in prediction errors for one-week forecasts, making it highly effective for short-term influenza forecasting. However, its performance declined for longer-term predictions, indicating limitations in accurately predicting flu trends beyond five to ten weeks.

The study [25] proposes a novel method for improving long-term influenza forecasts by leveraging worldwide surveillance data. The authors introduce a two-stage data selection approach, which first evaluates the predictive power of foreign surveillance data and then incrementally adds relevant data to improve the accuracy of influenza forecasts for a target country. This method, tested across multiple countries using six machine learning models, demonstrates that well-selected foreign data can enhance long-term forecasting performance. However, the study has limitations, particularly the dependency on the quality and consistency of surveillance data from various countries. Additionally, the proposed scheme requires validation set evaluation, which may not be robust if significant pattern differences exist between the validation and testing sets. This could impact the model's generalizability across diverse real-world settings.

Research [26] explores the development of a predictive model for influenza outbreaks in 12 French regions using a variety of data sources. The authors combine electronic health records (EHRs), web searches, Twitter data, and climate information to enhance the accuracy of real-time and short-term flu forecasts. Using an ensemble machine learning approach, the study finds that integrating these diverse data sources improves the model's performance in predicting ILI at the regional level. The ensemble model, called ARGONet, outperforms individual models, particularly for one- and two-week-ahead forecasts. However, the paper notes limitations, including the model's dependence on timely and high-quality data from all sources.

The paper [27] compares the performance of various time series forecasting models, XGBoost, ARIMA, and SARIMA, for predicting monthly influenza cases in Saudi Arabia. The study demonstrates that XGBoost outperforms both ARIMA and SARIMA models in terms of accuracy, particularly in capturing the nonlinear relationships in the data. By utilizing a comprehensive dataset from 2017 to 2022, the authors show that XGBoost provides superior forecasting with lower errors in metrics like MSE, MAE, and RMSE. However, a limitation of the study is its reliance on past seasonal data, which may not account for anomalies or significant changes in influenza trends, such as those caused by pandemics or environmental factors.

The study [28] introduces a novel deep learning model, SAIFlu-Net, designed for regional influenza forecasting. The model combines LSTM networks, which effectively capture time-series patterns, with a self-attention mechanism to identify similarities between regions' influenza occurrence patterns. This hybrid approach allows the model to improve both short- and long-term forecasting accuracy. The authors validate the model's performance on datasets from the U.S. and Japan, demonstrating that SAIFlu-Net outperforms several existing forecasting models, such as CNNRNN and Cola-GNN, regarding RMSE and Pearson correlation coefficient. Despite its strengths, the model shows reduced accuracy for longer-term forecasts, and the authors acknowledge that using only historical influenza data, without incorporating external factors like weather or social data, may limit its predictive power.

Research [29] examines the utility of combining deep learning models with traditional statistical approaches to improve influenza forecasting. The study leverages various models, including beta regression, ARIMA, LASSO, and multivariate adaptive regression splines (MARS), alongside a deep learning feedforward neural network (FNN). By employing Bayesian model averaging (BMA) to fuse these models, the authors aimed to enhance the accuracy of both point and probabilistic forecasts for ILI in Dallas County. The results show that the ensemble approach using BMA with continuous ranked probability score as weights outperforms individual models, particularly in one- and two-week ahead predictions. However, a limitation of this study is its reliance on historical data and the exclusion of spatial factors, which may reduce its generalizability across different regions.

The paper [30] proposes a framework for improving the accuracy of influenza forecasts by combining multiple data sources, including public health surveillance data, EHR, internet search traffic, and social media activity. The authors employ a hierarchical framework using multi-linear regression and greedy optimization to select the most predictive combination of data sources. The results show that combining public health surveillance data with EHR data significantly enhances forecast accuracy. In contrast, though abundant, internet and social media data do not contribute as much to predictive performance. One key limitation of the study is the exclusion of real-time social media and search data in the final model, which may miss timely signals during influenza outbreaks.

In light of the analysis of recent studies, it is clear that machine learning models, especially when combined with diverse data sources, offer substantial improvements in influenza forecasting accuracy. However, many existing approaches, such as those leveraging social media, search engine queries, or electronic health records, face limitations regarding data quality, real-time availability, and generalizability across regions. Our study focuses on developing a forecasting model specifically tailored to the unique conditions in the war-affected Kharkiv Oblast of Ukraine. The challenges posed by disrupted healthcare systems, displaced populations, and altered social dynamics require a model that can accurately predict influenza trends in such a complex environment. While previous studies have highlighted the potential of machine learning models, particularly LSTM, for forecasting influenza, their applications have been largely limited to stable environments with consistent data.

Our research aims to address this gap by utilizing the LSTM deep learning approach, which excels at capturing temporal dependencies, to forecast influenza outbreaks in a setting where traditional data sources may be unreliable or incomplete. This focus on a conflict zone not only fills a critical gap in the current body of research but also offers insights into how advanced machine learning techniques can support public health efforts in crises.

3. Materials and Methods

The LSTM network is a type of RNN designed to capture long-term dependencies in sequential data, making it ideal for time-series forecasting, such as influenza incidence prediction. LSTMs address the limitations of traditional RNNs, particularly issues with vanishing or exploding gradients, by using specialized gates, forget, input, and output gates, that control the network's information flow [31]. This allows the model to selectively remember, update, or discard information at each time step.

The forget gate determines which information from previous time steps should be discarded. It allows the model to remove irrelevant data while retaining important historical information necessary for future predictions.

The input gate decides which information should be added to the cell state. This ensures that only relevant new data is incorporated into the network's memory at each time step.

The output gate controls which part of the cell state will be used as the output for the current time step, ensuring that the most relevant information is passed on for prediction.

For this study, we trained the LSTM model using monthly influenza incidence data from January 2013 to April 2024 in the Kharkiv Oblast. The data was split into training, validation, and testing sets, ensuring the model was evaluated on unseen data to assess its generalization capabilities.

We implemented dropout as a regularization technique to reduce overfitting, a common issue in deep neural networks. Dropout involves randomly "deactivating" a proportion of neurons and their connections during each training iteration. By disabling different neurons in each iteration, the network is forced to learn more generalized data patterns instead of memorizing the training set. After training, all neurons are reactivated for prediction. Dropout was controlled by a parameter that sets the probability of neuron deactivation, ensuring the model avoids overfitting while maintaining robust performance.

The model was trained using the Adamax optimizer, a variant of the Adam optimizer, which is particularly well-suited for large, high-dimensional datasets. Adamax improves on Adam's adaptive learning rate capabilities, allowing for more efficient convergence during training. During the training process, we experimented with several configurations of hyperparameters, including batch size, number of epochs, and LSTM units. Specifically, we tested LSTM units of 4, 8, 16, 32, and 64, and ran the model for 400, 450, and 500 epochs. These hyperparameters were fine-tuned using an empirical approach tailored to the specific characteristics of the dataset.

We used mean squared error (MSE) as the loss function to optimize performance, measuring the difference between the predicted and actual influenza incidence values. Regular backpropagation through time (BPTT) was used to update the network's weights, allowing the model to learn from previous prediction errors and adjust its parameters accordingly.

The combination of LSTM's sequential learning capability, dropout regularization, and the Adamax optimizer enabled the model to efficiently learn and predict influenza trends in the war-affected Kharkiv Oblast, focusing on minimizing overfitting and maximizing generalizability across different periods.

For this experimental study, we utilized monthly influenza incidence data from January 2013 to April 2024 in the Kharkiv Oblast, sourced from the Kharkiv Oblast Centre for Disease Control and Prevention. Figure 1 presents a histogram of the distribution of new influenza cases in the Kharkiv oblast.

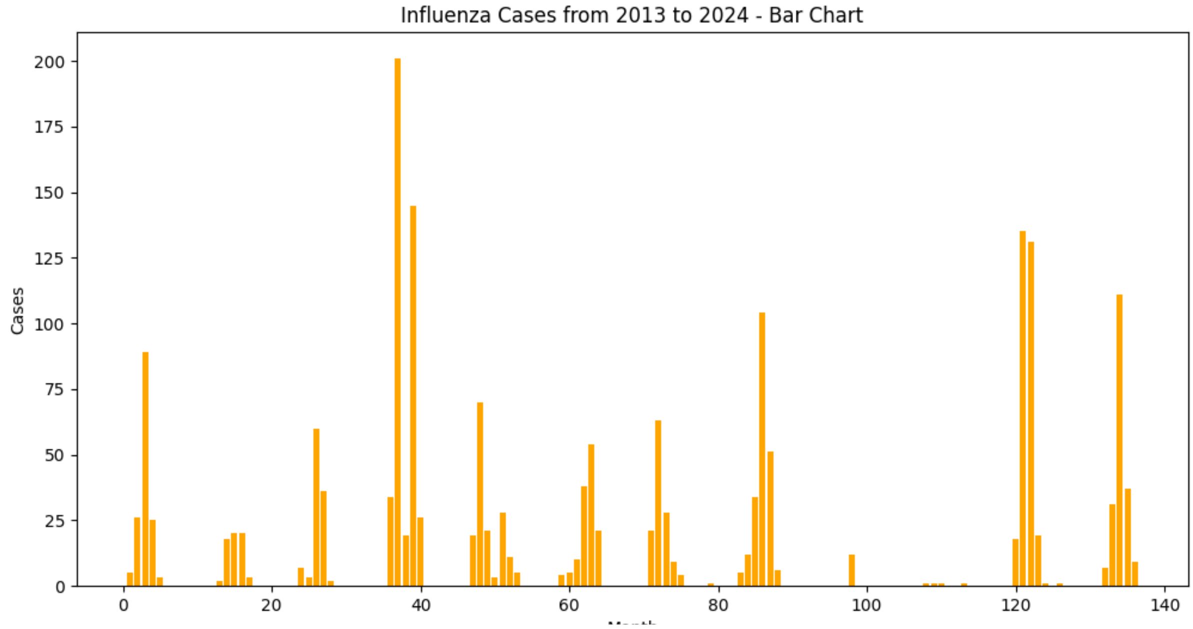

Figure 1: Histogram of new influenza cases in Kharkiv oblast.

Figure 2 presents the local peaks of new cases of influenza in the Kharkiv oblast.

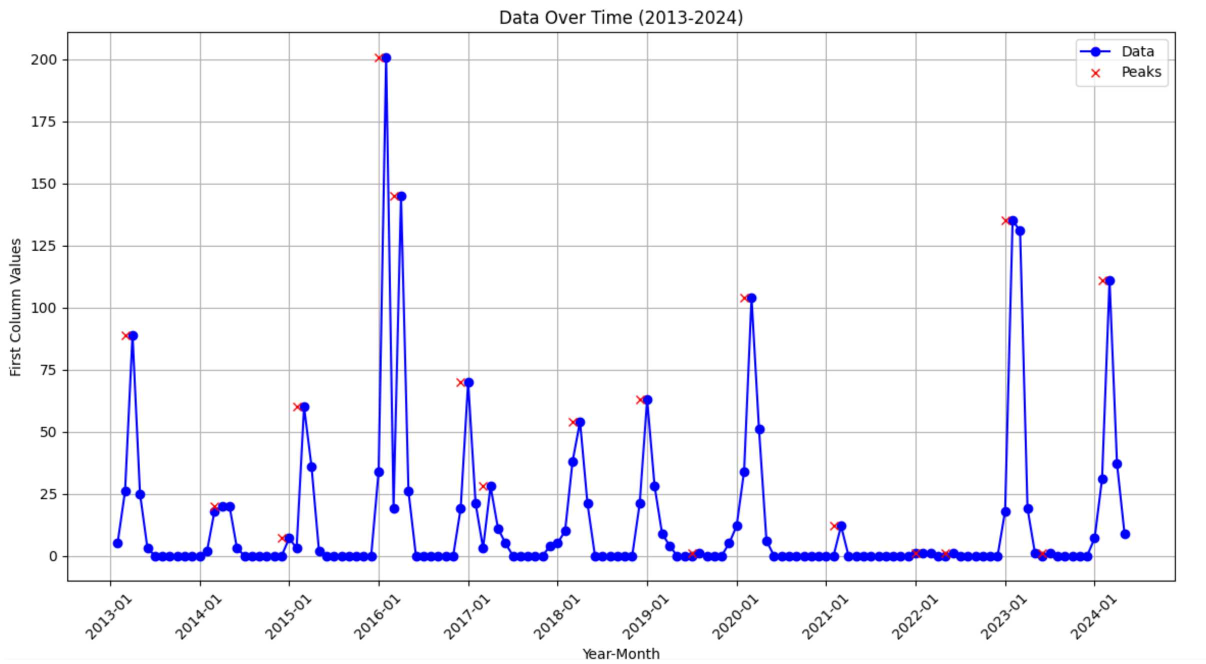

Figure 2: The local peaks of new influenza cases in Kharkiv oblast.

4. Results

Figure 3 presents the forecasted dynamics of influenza in Kharkiv oblast. The blue line represents the incidence data, while the red line shows the predicted values. The model demonstrates an overall ability to capture the patterns of influenza outbreaks, particularly during peak incidence periods. There is a noticeable alignment between the predicted and actual values, especially during the sharp increases and decreases in case numbers. However, some discrepancies are observed during the peaks, where the predicted values slightly underestimate the actual data.

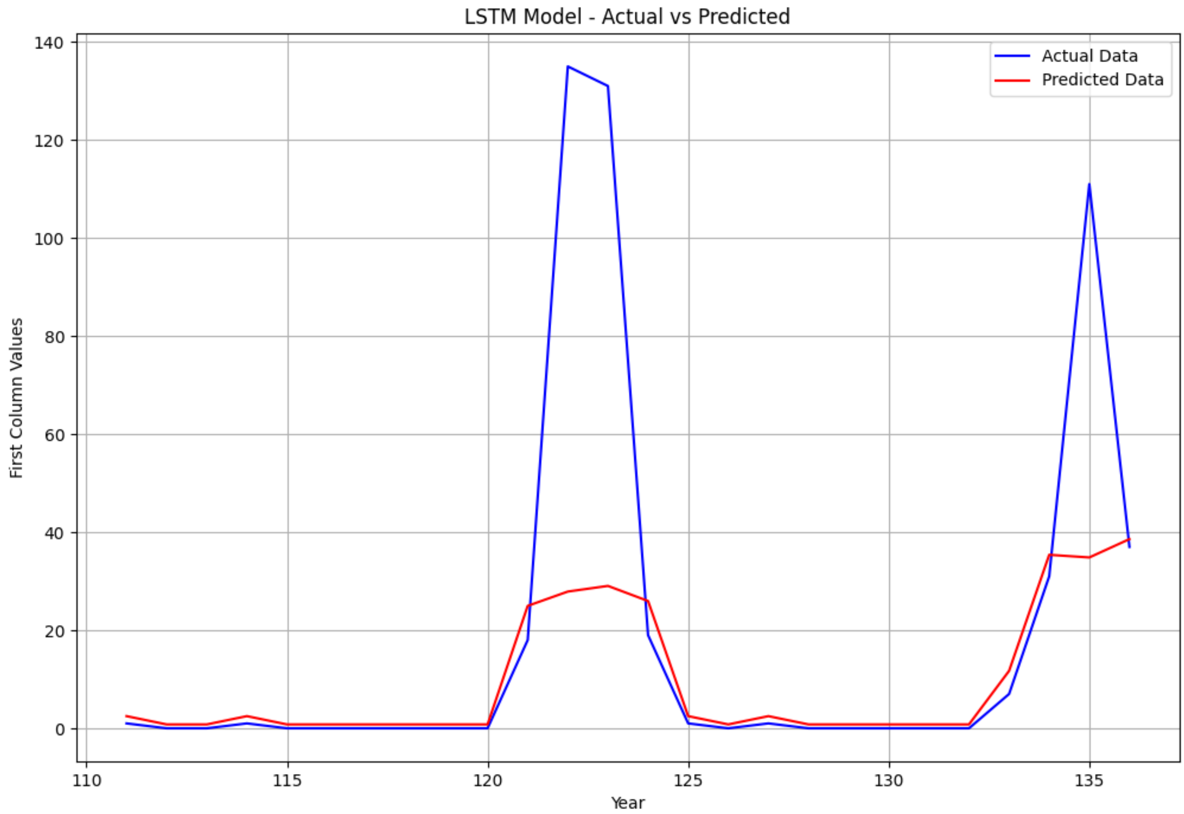

Figure 3: The forecast of new influenza cases in Kharkiv oblast.

Table 1 shows the model's best hyperparameters. These parameters were fine-tuned empirically to achieve optimal performance.

Table 2
The model's best hyperparameters

Hyperparameter	Value
Units	4
Dropout	250
Optimizer	Adamax

Table 2 shows the model performance.

Table 2
The model's performance

Metric	Value
Best MSE	0.0255
Best MAPE	6.3976
Best MAPE inv	27.2086

5. Discussion

This study aimed to develop an LSTM-based model for forecasting influenza outbreaks in the war-affected Kharkiv Oblast, Ukraine, where traditional healthcare systems have been severely disrupted due to the ongoing conflict. The study's results highlight the LSTM model's effectiveness in predicting the short-term dynamics of influenza incidence, particularly during peak transmission periods. The model's ability to capture temporal dependencies in the data is reflected in the close alignment between predicted and actual case numbers, especially during sudden surges in influenza incidence. The model achieved a best Mean Squared Error (MSE) of 0.0255 and a Mean Absolute Percentage Error (MAPE) of 6.3976, demonstrating high accuracy in forecasting short-term influenza trends. These results suggest that the LSTM model has strong potential for providing real-time predictions that can inform public health interventions.

The scientific novelty of this study lies in its application of the LSTM model within a conflict-affected region. This context has not been extensively explored in previous research on influenza forecasting. Most prior studies in this field have focused on stable regions where healthcare data collection systems function consistently. However, healthcare systems are under immense strain in war-affected areas like Kharkiv Oblast, and data collection may be irregular or incomplete. This study demonstrates the adaptability of LSTM models to handle such challenges, providing accurate predictions even when traditional data collection methods are disrupted. The application of machine learning in a volatile and crisis-stricken environment highlights the robustness of the LSTM approach, which can process fragmented data while still producing reliable forecasts.

Another innovative aspect of this study is its focus on forecasting influenza in a region experiencing large-scale population displacement, overcrowded shelters, and limited access to healthcare services. Including data from a war zone adds complexity to the model's predictions, as influenza transmission patterns in such regions may differ significantly from those in more stable environments. The ability of the LSTM model to account for and predict outbreaks in this challenging setting represents a significant contribution to the field of infectious disease modelling, particularly for regions affected by conflict or other crises.

The practical novelty of this research is its potential to provide actionable insights for public health authorities operating in conflict-affected regions. By offering real-time and accurate forecasts of influenza outbreaks, the LSTM model can assist public health officials in making informed decisions regarding resource allocation, vaccination campaigns, and healthcare planning. In a region like Kharkiv Oblast, where healthcare infrastructure is compromised, such predictive models are crucial for optimizing the limited resources available to address public health needs. Accurate short-term forecasts can help ensure that medical supplies, vaccines, and healthcare personnel are effectively deployed, particularly during peak influenza transmission periods.

Moreover, the model’s application extends beyond Ukraine, offering valuable lessons for other regions facing similar challenges. For instance, conflict zones in the Middle East, Africa, and other parts of the world, where healthcare systems are similarly disrupted, could benefit from implementing machine learning models like LSTM to forecast outbreaks of infectious diseases. Using such models in conflict or crisis scenarios represents a shift towards data-driven decision-making, even when data is fragmented or unreliable.

Despite its promising results, the study has several limitations that should be addressed in future research. One significant limitation is the model’s reduced accuracy over longer time horizons. Like many machine learning models used for time-series forecasting, the LSTM model performed well in short-term predictions but struggled to maintain accuracy for forecasts extending several weeks into the future. This limitation is consistent with findings from other studies that have employed LSTM for disease forecasting. Future research could explore hybrid models that combine LSTM with other machine learning or statistical approaches to improve long-term forecasting accuracy.

Another limitation of the study is its reliance on the quality and completeness of the available data. While the LSTM model is robust in handling sequential data, its performance still depends on the availability of accurate and timely data inputs. In conflict zones like Kharkiv Oblast of Ukraine, data collection is often disrupted, leading to potential gaps in the dataset. Incomplete data can reduce the model's effectiveness and lead to unreliable forecasts. This limitation could be addressed by incorporating real-time data sources, such as mobility data from mobile phones or satellite data, which could provide additional insights into population movement patterns and their impact on influenza transmission.

6. Conclusions

This study developed an LSTM-based model to forecast influenza outbreaks in the war-affected Kharkiv Oblast, Ukraine, where the ongoing Russian full-scale invasion has severely impacted the healthcare infrastructure. The model's ability to provide accurate short-term forecasts, as evidenced by its low MSE and MAPE values, underscores its potential for application in regions where timely and reliable public health data is scarce or incomplete. This research demonstrated that LSTM networks, which are well-suited for handling sequential data, can be effectively applied to predict disease transmission dynamics even in highly disrupted environments.

A key contribution of this study is its novel application of LSTM in a conflict zone, expanding the scope of machine learning in public health forecasting to settings where data collection systems are often unreliable. The model's successful adaptation to the challenges posed by such a region provides a robust framework for predicting influenza and potentially other infectious diseases in crises. This capability is crucial for public health decision-making, particularly in regions facing complex social and healthcare challenges.

Looking forward, future research should address the limitations of this study by improving long-term forecasting accuracy. This could involve combining the LSTM model with other forecasting methods or integrating additional data sources such as real-time mobility, environmental, or social data to capture better the full spectrum of factors influencing influenza transmission. Moreover, extending the application of this model to other infectious diseases in similarly affected regions would enhance its utility in public health management. Further validation of the model in different settings, particularly those experiencing large-scale humanitarian crises, will also be essential for confirming its generalizability and broadening its global relevance.

This study significantly contributes to disease modelling by demonstrating the practical utility of LSTM networks for influenza forecasting in a war-affected region. The results open the door to further innovations in machine learning applications for public health, particularly in environments where traditional healthcare data and infrastructure are compromised.

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8. Declaration on Generative AI

During the preparation of this paper, the authors used ChatGPT and Grammarly in order to identity and correct grammatical errors, typos, and writing mistakes. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

9. References

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