

Data-Driven Approach for Influenza-Like Illness Forecasting Using ML Classifiers

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ABSTRACT

Effective prediction of Influenza-Like Illness (ILI) is critical for timely response from the public health sector, however, the traditional models of surveillance depend mostly on past number of cases and neglect environmental factors that influence the spread of disease. Influenza-Like Illness (ILI) forecasting is an important part of early response from the public health sector. This paper utilizes a combination of CDC records of ILI surveillance and regional weather to predict ILI patterns. Three models - ARIMA, XGBoost, and LSTM were used and compared. XGBoost showed the best performance, followed by LSTM and much worse performance of ARIMA. The findings indicate that a combination of weather information and past trend in cases, along with non-linear models, improve the prediction of ILI.

Keywords: ARIMA, epidemiological surveillance, influenza-like illness, LSTM, outbreak prediction, time-series forecasting, XGBoost

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1. INTRODUCTION

Influenza-like Illness remains one of the major respiratory disease burdens worldwide, causing significant morbidity, healthcare burden, and economic loss annually. Public health organizations such as the CDC operate comprehensive surveillance systems which release reports about ILI percentages per week in various regions. Nevertheless, the inherently reactive approach of conventional reporting systems constrains the amount of time for preparing for the outbreak. Short-term and medium-term forecasts of ILI activity can help public health authorities be better prepared to provide vaccines in advance, staff emergency rooms accordingly, and make appropriate public notifications. Apart from case history trends, there is a wide body of epidemiology research that has shown that environmental conditions, especially temperature and humidity, have a direct impact on virion longevity and infectivity, as well as indirect effect on human behavior and crowding indoors. It forms the basis of the current research project, which assumes that combining surveillance signals and meteorological factors can yield improved predictions compared to case-history-based models.

The existing literature on ILI prediction has primarily concentrated on (i) classical statistical time series models such as ARIMA, which fail to capture the non-linear and regime changing characteristic of epidemic curves or (ii) deep learning models like LSTM, which have relied heavily on historical data, Google queries and social media. Very few papers have rigorously benchmarked tree based ensemble algorithms such as XGBoost with classical and deep sequential models in a unified weather-augmented feature space. Additionally, existing workflows often lack transparency in terms of converting the huge heterogeneous dataset of surveillance-weather into a small number of weekly features. This paper attempts to address this issue by presenting a workflow that combines CDC ILI data with regional weather data, engineering lagged and normalized features and comparing ARIMA, XGBoost and LSTM under identical conditions.

The main contributions of this paper are:

- Construction of a merged CDC ILI-weather master dataset (9,018 records, 23 features) and its systematic transformation into a feature-engineered weekly dataset (164 records, 12 features) suitable for supervised timeseries learning.

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- Design and implementation of a weather-augmented feature set incorporating temperature, humidity, pressure, wind speed, and multi-week lagged ILI percentages.
- Empirical correlation analysis quantifying the linear relationship between meteorological covariates and target ILI percentage, informing feature selection decisions.
- Comparative benchmarking of three forecasting paradigms, ARIMA, XGBoost, and LSTM, under a common train-test split and identical error metrics (RMSE, MAE, MAPE).
- A consolidated performance heatmap and multi-model visualization framework enabling direct qualitative and quantitative comparison of forecasting behavior across sudden seasonal upswings.
- Identification of ensemble and recurrent architectures as superior to classical statistical baselines for capturing the non-linear, regime-shifting dynamics of ILI outbreaks.

II. RELATED WORK

Forecasting of influenza-like illness has been studied extensively across statistical, machine learning, and deep learning paradigms. This section organizes the reviewed literature into three thematic categories.

A. Machine Learning and Ensemble Approaches

Several studies have explored the use of search-engine and social-query data combined with tree-based or classical machine learning models to forecast ILI activity. Olukanmi et al. compared deep learning, classical machine learning, and time-series models using Google search trends for South African ILI forecasting, finding that advanced learners generally outperformed traditional baselines, though performance remained sensitive to digital-access biases in search behavior [4]. Similarly, work combining multiple regression models with artificial neural networks has demonstrated that hybrid statistical-ANN surveillance can track influenza activity more flexibly than regression alone, albeit with limited discussion of input variable selection and overfitting control [10]. Wei et al. employed a three-layer LSTM enriched with Baidu search indices, using Pearson correlation to preselect the most relevant query terms, and reported that the addition of search-derived covariates meaningfully reduced RMSE relative to ILI-only baselines [18], reinforcing the value of auxiliary covariate integration that this paper extends to meteorological data.

B. Deep Learning in Epidemiological Forecasting

Deep sequential architectures, particularly LSTM networks and their variants, have become the dominant paradigm for capturing temporal dependencies in ILI time series. Dong et al. proposed SMILE, a multi-scale time-series model enhanced with GPT-2-derived semantic features fused via crossattention, achieving the lowest reported average MSE and MAE across multiple

forecasting horizons among compared architectures [1]. Hole et al. demonstrated that a bidirectional LSTM with dropout and L2 regularization achieved an MAE of 0.077 and R^2 of 0.9743 on percent-ILI data, outperforming ARIMA, standard LSTM, and Random Forest baselines [2]. Shaghaghi et al.'s eVision framework combined CDC/WHO surveillance with Google Trends queries in an LSTM model, achieving a SMAPE of approximately 0.0985 (about 90.15% accuracy) over a seven-week horizon, while noting reduced transferability when applied internationally [11]. Papagiannopoulou et al. introduced ReILIF, an LSTM-based architecture fusing meteorological time series with static population covariates and inter-regional self-attention, which outperformed Cola-GNN, SAIFlu-Net, and Temporal Fusion Transformer baselines for long-horizon (10+ week) regional forecasting [7]. Li et al. proposed a Convolutional LSTM (CLSTM) encoder-decoder incorporating variational mode decomposition and transformer-based keyword fusion, reporting substantial accuracy gains when explicitly separating epidemic and non-epidemic seasons [13]. Venna et al. presented a datadriven LSTM model incorporating environmental predictors such as air pollution and climatic variables alongside geographic proximity, demonstrating measurable RMSE improvements over ARIMA and standard LSTM baselines across ten CDC-HHS regions [8], forming a direct conceptual precedent for the weather-augmented approach adopted in this study.

C. Time-Series and Statistical Methods

Classical statistical approaches remain widely used as baselines due to their interpretability and low data requirements. Autoregressive and moving-average models have been applied to ILI mortality surveillance since the early 1980s, though their linear assumptions limit their responsiveness to sudden nonlinear outbreak surges. Hybrid ARIMA-LSTM architectures, which decompose the linear and non-linear components of the ILI signal, have been proposed to combine the interpretability of ARIMA with the non-linear modeling capacity of LSTM, though quantitative gains reported in the literature vary by region and season [15]. Network-based descriptive approaches, such as time-series visibility graphs combined with community-detection algorithms, have also been used to segment influenza history into discrete epidemiological stages, achieving high modularity scores, although such methods remain descriptive rather than predictive in nature [12]. Spatial-statistical techniques, including Moran's I and Geary's C combined with GIS-based features, have further been integrated with machine learning to capture geographic autocorrelation in disease hotspot identification [16], motivating future extensions of the present framework toward spatially-aware modeling.

III. PROPOSED METHODOLOGY

A. Data Acquisition and Preprocessing

The proposed pipeline begins with a merged master dataset, `cleaned_ili_master.csv`, containing 9,018 regionweek records across 23 attributes. This master dataset integrates CDC ILI surveillance fields, including

region type, state, year, week, weighted ILI percentage, age-stratified case counts (ages 0–4, 5–24, 25–49, 25–64, 50–64, 65+), the number of reporting providers, and total patient counts, with regional meteorological observations comprising temperature, humidity, atmospheric pressure, wind direction, and wind speed. Three lagged ILI percentage features (ili_pct_lag_1, ili_pct_lag_2, ili_pct_lag_3) were also computed to encode short-term autoregressive memory.

Given the heterogeneity and regional granularity of the master dataset, a second-stage transformation was applied to produce `final_processed_ili_weekly.csv`, a compact, model-ready weekly dataset of 164 chronologically ordered observations across 12 engineered features: year, week, target ILI percentage, temperature, humidity, pressure, wind speed, ILI case counts, total patients, and the three lagged

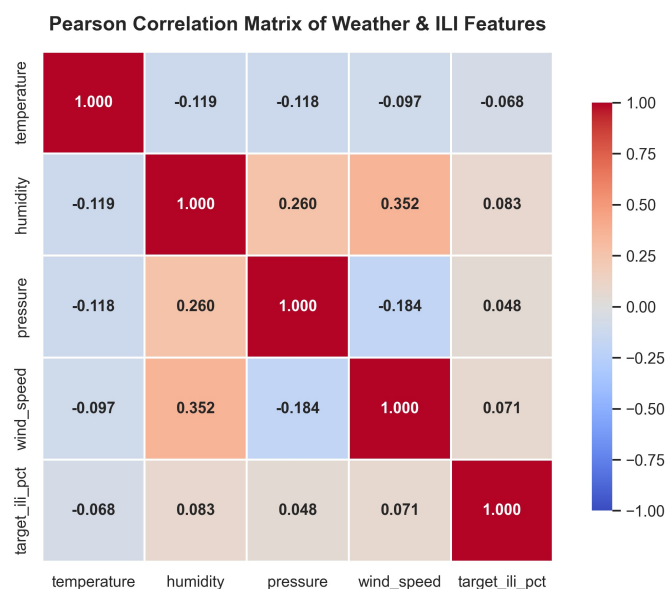


Fig. 1. Pearson correlation matrix of weather covariates and target ILI percentage.

ILI percentage terms. This transformation entailed combining region-level records into weekly consolidated observations, filling in gaps through linear interpolation where needed, scaling numerical variables to ensure uniformity, and matching up meteorological readings with their respective epidemiological weeks. This results in a data set that retains its time dependency while at the same time dramatically reducing its dimensionality.

B. Correlation and Feature Selection

To determine the existence of any linear correlation between the meteorological covariates and the target ILI percentage, a Pearson Correlation Matrix was calculated using the weekly dataset as shown in Figure 1. Results reveal only weak linear relationships. Humidity has the highest correlation with the target ILI percentage ($r = 0.083$) followed by windspeed ($r = 0.071$) and pressure ($r = 0.048$) whereas temperature has a negative weak correlation ($r = -0.068$). Interestingly enough, humidity

and windspeed also have a moderate positive correlation ($r = 0.352$), and humidity and pressure are correlated ($r = 0.260$), indicating interdependence amongst the weather covariates rather than any direct linear relationship to the ILI activity. Since the relationships were weak and indicated no linear association, this implies that the meteorological covariates have non-linear effects on the ILI activity, hence, the use of all the four weather covariates in the engineered feature set for the non-linear XGBoost and LSTM model, following previous literature on non-linear effects of temperature and humidity on the influenza virus transmissibility.

C. System Architecture and Workflow

Figure 2 provides the overall workflow for the proposed system, from data acquisition to preprocessing, feature engineering, training of models, evaluation, and output visualization.

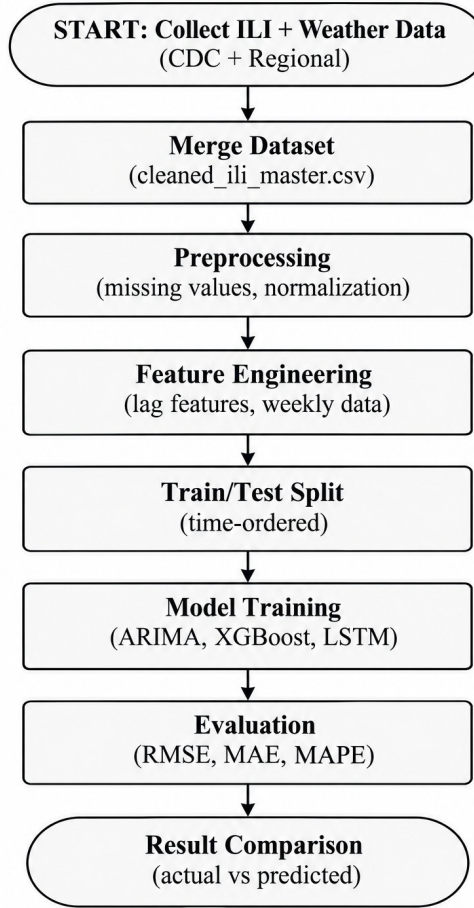


Fig. 2. System workflow of the proposed ILI forecasting pipeline.

The pipeline begins by acquiring the CDC surveillance data in conjunction with local weather data and then moves on to the preprocessing step that handles the missing values via linear interpolation and normalization of numeric features. The next step involves feature engineering where the lagged ILI terms are generated and the dataset is converted into its weekly form. Finally, the preprocessed dataset is partitioned into train and test sets while maintaining temporal causality. The three models are trained separately with the same features. Model outputs are then evaluated using regression metrics and visualized in comparison.

D. Predictive Models

1) **ARIMA:** Autoregressive Integrated Moving Average (ARIMA) model represents the differenced ILI series y_t as a linear combination of its past terms as well as past forecast errors:

$$\left(1 - \sum_{i=1}^p \phi_i L^i\right) (1 - L)^d y_t = \left(1 + \sum_{j=1}^q \theta_j L^j\right) \varepsilon_t \quad (1)$$

where L is the lag operator, p and q represent the orders of autoregressive and moving average respectively, d is the order of differencing done to make the series stationary, ϕ_i and θ_j are the ARIMA model parameters, and ε_t is the error term. ARIMA was used as the classical statistics

benchmark model for this research, which is linear compared to the non-linear learners.

2) **XGBoost:** XGBoost constructs an additive ensemble of K regression trees, where the prediction for observation i is given by:

$$\hat{y}_i = \sum_{k=1}^K f_k(\mathbf{x}_i), \quad f_k \in \mathcal{F} \quad (2)$$

with $\mathcal{F}$ the space of regression trees and $\mathbf{x}_i$ the feature vector comprising lagged ILI percentages, temperature, humidity, pressure, and wind speed. Training proceeds by minimizing a regularized objective:

$$\mathcal{L}(\phi) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (3)$$

where $l(\cdot)$ is a differentiable convex loss (mean squared error in this study) and $\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \|w\|^2$ penalizes tree complexity through the number of leaves T and leaf weights w , controlling overfitting on the relatively compact 164-observation weekly dataset.

3) **LSTM:** The LSTM network processes sequential windows of past stock and weather features through a gated memory cell. At each time step t , the forget, input, and output gates are computed as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (4)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i), \quad o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (5)$$

$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C) \quad (6)$$

where $\sigma(\cdot)$ is the sigmoid activation, $\odot$ denotes the Hadamard product, x_t is the input feature vector at time t (lagged ILI and weather covariates), and h_t is the hidden state passed to subsequent dense layers to output the forecasted ILI percentage. The network was trained on the Adam optimizer with the loss function being the mean squared error over time windows built from the weekly

feature set. This allowed the network to learn both short term and long term dynamics within the ILI signal.

Table I highlights the input variables and important configurations for each of the three models.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Setup and Metrics

All three models were trained and tested on the dataset `final_processed_ili_weekly.csv` using the same, time-based, train-test split to maintain causality and avoid any information contamination from future weeks during training. Model performance was measured by three complementary regression performance metrics:

Table I: Model Configuration Summary

Model	Key Configuration	Input Features
ARIMA	Order (p,d,q) selected via stationarity testing	Univariate ILI % series
XGBoost	Squared-error loss; treedepth and leaf regularization tuned	Lagged ILI % + weather co-variates
LSTM	Adam optimizer; MSE loss; sliding time windows	Lagged ILI % + weather co-variates

Table II: Model Performance Comparison On Test Set

Model	RMSE	MAE	MAPE (%)	7-Day	14-Day
LSTM	0.2200	0.1256	8.6373	5.2742	5.0245
ARIMA	0.6473	0.5080	50.4614	0.9023	0.6934
XGBoost	0.1534	0.1059	7.4319	4.6401	4.5057

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (8)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (9)$$

$$\text{MAPE} = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (10)$$

where y_i is the actual and $\hat{y}_i$ the predicted ILI percentage of the i observation, while n is the number of test observations. Alongside one-step ahead error metrics, 7 day and 14 days ahead forecast error metrics were also calculated to evaluate short horizon forecasting abilities of the models.

B. Performance Evaluation and Comparative Analysis

Table II and Figure 3 summarize the comparative performance of ARIMA, XGBoost, and LSTM across all evaluation metrics.

The results indicate that XGBoost achieves the strongest overall performance, attaining the lowest RMSE (0.1534), MAE (0.1059), and MAPE (7.43%) among the three models, narrowly ahead of LSTM. ARIMA exhibits a markedly higher MAPE (50.46%), a consequence of the model's linear structure struggling to track the sharp non-

linear surge in ILI percentage observed toward the end of the test horizon.

Figure 4 presents the actual versus predicted ILI percentage trajectory for the LSTM model over the test period. The predicted curve closely tracks the actual series through the lowactivity weeks (indices 0–20) and continues to follow the steep late-season upswing, though with a slight lag in magnitude during the final weeks, consistent with the sequential model's reliance on recent historical windows.

Figure 5 shows the corresponding XGBoost actual-versus-predicted plot, which tracks the actual series with the tightest

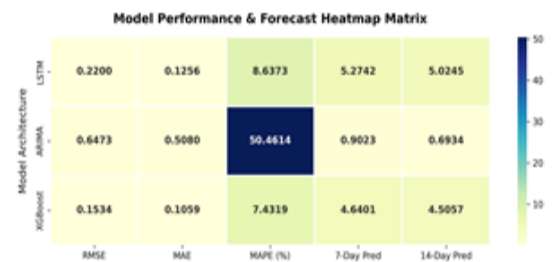


Fig. 3. Model performance and forecast heatmap matrix across RMSE, MAE, MAPE, and 7/14-day forecast horizons.

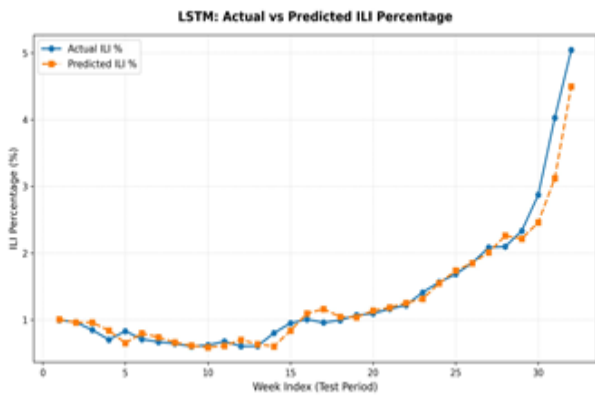


Fig. 4. LSTM: actual versus predicted ILI percentage over the test period.

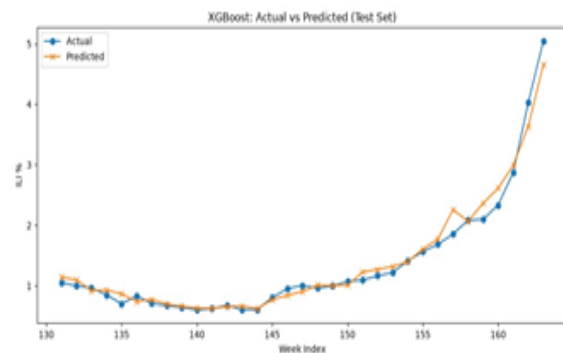


Fig. 5. XGBoost: actual versus predicted ILI percentage over the test period.

overall alignment among the three models, including during the sharp late-horizon increase, corroborating its superior quantitative metrics.

Figure 6 compares all three methods to the truth on the complete test period. It is clear from the graph that whereas the ARIMA method copes with the moderate mid-range variations fairly well, it significantly underestimates the ILI percentage for the low activity period (giving almost zero and even negative results during weeks 7–13), and then overestimates the values during the ascending stage. In contrast, both XGBoost and LSTM remain closely aligned with the actual curve throughout the trough and the rising phase, only beginning to under-predict slightly during the final, steepest weeks of the outbreak surge, where the true ILI percentage rises sharply to approximately 5%.

Overall, the comparative analysis demonstrates that nonlinear learners, both the ensemble tree-based XGBoost model and the recurrent LSTM network, substantially outperform the classical ARIMA baseline in capturing the regime-shifting, seasonal-surge behavior characteristic of ILI activity. The marginal edge of XGBoost over LSTM on this comparatively small 164-observation weekly dataset suggests that tree-based ensembles may generalize more efficiently under limited training data, whereas LSTM's advantage would likely become more pronounced with a larger volume of historical weekly observations. The weak linear correlations observed between individual

weather covariates and target ILI percentage (Figure 1), combined with the strong performance of the non-linear models, together support the conclusion that meteorological influence on ILI activity is realized through non-linear and interaction effects rather than simple additive linear relationships.

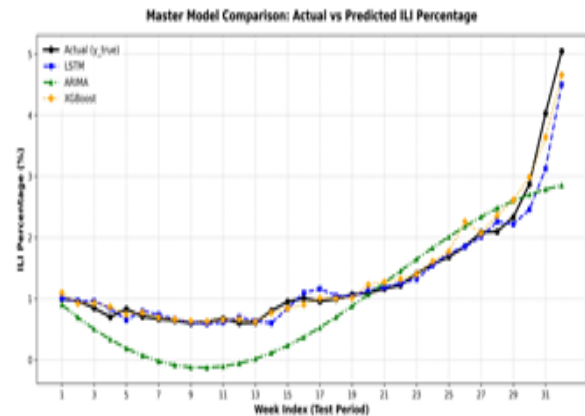


Fig. 6. Master model comparison: actual versus predicted ILI percentage for LSTM, ARIMA, and XGBoost.

V. CONCLUSION AND FUTURE WORK

This paper presented a weather-augmented forecasting framework for Influenza-Like Illness that integrates CDC surveillance data with regional meteorological covariates, and systematically benchmarks ARIMA, XGBoost, and LSTM models on a feature-engineered weekly dataset. Experimental results demonstrate that both XGBoost (RMSE = 0.1534,

MAPE = 7.43%) and LSTM (RMSE = 0.2200, MAPE =

8.64%) substantially outperform the classical ARIMA baseline (RMSE = 0.6473, MAPE = 50.46%), particularly during nonlinear seasonal transitions where linear models fail to extrapolate the outbreak trajectory. Correlation analysis further reveals that weather covariates exhibit only weak linear association with ILI percentage individually, underscoring the importance of non-linear model architectures for extracting predictive value from meteorological data. These findings support the practical adoption of ensemble and recurrent learning approaches within operational, weather-informed epidemiological early-warning systems.

Future work will extend this framework along several directions: (i) incorporating additional exogenous covariates such as vaccination coverage, population mobility, and airquality indices; (ii) extending the regional weekly dataset to a multi-region, spatially-aware model using graph neural networks or spatial attention mechanisms to capture inter-regional transmission dynamics; (iii) exploring hybrid ARIMA–LSTM and transformer-based architectures (e.g., FinBERT-style or GPT-derived semantic encoders applied to public health news) to combine interpretability with non-linear representational capacity; and (iv) deploying the framework within a realtime dashboard for continuous retraining and early-warning alerting, analogous to

interactive visualization systems adopted in related sentiment-augmented forecasting domains.

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