TIME SERIES ANALYSIS
Short-term temperature forecasting using ARIMA and LSTM models

Team No .12

Submitted by-

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I. INTRODUCTION

The aim of the on-going study is to differentiate the raising demand for precise weather forecasts in numerous areas, that includes transportation, management, urban development, energy, and agriculture that motivated this research.

Data preprocessing, individual ARIMA and LSTM model implementation, hybrid ARIMA-LSTM model development, comparison analysis, and testing across several time scales and climatic circumstances are all part of the methodology. This strategy seeks to improve temperature forecasting methods by providing a more complex way to foresee short-term variations with repercussions, for the companies that rely on accurate temperature forecasts.

The technique involves collecting the data, implementing the model, comparing the results, and thoroughly assessing the process. The goal of the study is to focus on forecasting method's precision, dependability, and effectiveness in a range of scenarios. This thorough examination will shed light on the usefulness of various prediction techniques in actual situations. The study looks at the advantages and disadvantages of each strategy to provide useful advice for choosing the best forecasting instruments for various industries and environmental circumstances.

The findings of this research have broad ramifications. By identifying the forecasting systems that perform best under given conditions, we can assist weather-affected businesses in making better judgments. This could lead to faster vitality dispersion, better agrarian edits administration, more successful asset assignment, and safer urban planning and transportation methods. Our goal with this investigation is to see through the advanced machine learning approaches and traditional factual procedures in temperature estimation, that results in more precise and reliable short-term climate forecasts.

II. PROBLEM DEFINITION

We present a hybrid prediction method that uses both statistical and deep learning methods to address the problem of accurate short-term temperature forecasting in various geographical regions of the U.S. Analyzing 35 major U.S. cities with varying climate zones from 1948 to 2022, the project's objective is to analyze seasonally based trends, compare forecasting methods, and develop a robust and scalable prediction model.

The three strategies examined are ARIMA for the straight drift and regularity, LSTM for non-linear conditions, and a crossover ARIMA-LSTM demonstrate that typifies the benefits of both strategies. This crossover framework makes strides upon the exactness of person standalone strategies, compensating for the downsides of both and territorial climate variety. In businesses such as urban plan, vitality communications, agribusiness, and transportation, precise temperature forecasts are basic

for decision-making and operational productivity, making this work profoundly advantageous. Critical for decision-making and operational efficiency, making this work highly beneficial.

III. LITERATURE SURVEY

Focusing on ARIMA models, LSTM models and hybrid methods, the study focuses on recently developed methods on time series forecasting and weather prediction.

1. **Linear Forecasting Model of ARIMA:**
   ARIMA models properly captured the seasons and regularities in time series data. Murat et al. demonstrated how well the ARIMA forecasted daily weather data, obtaining a mean absolute percentage error (MAPE) of 3.2% for temperature predictions in the 2018 research analysis. Ye et al. (2018), however, emphasized ARIMA's shortcomings when dealing with non-linear data, hence demonstrating the necessity for more sophisticated methods.

2. **LSTM Networks for Dependencies:**
   Nonlinear time patterns in weather forecasts can be well represented by LSTM models (2018) found that using LSTM instead of ARIMA increases the RMSE by 84% to 87% for various time series forecasting operations. De Sa & Ranatunga (2021) further demonstrated the superiority of LSTM, with an overall RMSE 15% lower than ARIMA, especially in situations with rapid temperature fluctuations. Nonlinear time patterns in weather forecasts can be well represented by LSTM models (2018) found that using LSTM instead of ARIMA increases the RMSE by 84% to 87% for various time series forecasting operations. Later, De Sa & Ranatunga (2021) demonstrated the advantages of LSTM, in situations with rapid temperature fluctuations with an overall RMSE 15% lower than ARIMA.

3. **Hybrid ARIMA-LSTM Approaches:**
   Recent studies have shown promising results when combining ARIMA and LSTM models, compared to a standalone model we demonstrated that a hybrid ARIMA-LSTM model diminishes RMSE by 20%. Abdullah et al (2020) enhanced this approach, demonstrating a 25% improvement in forecast accuracy compared to traditional methods across a range of weather parameters compared to conventional methods.

4. **Research Gaps and Our Contributions:**
   Our assessment of the literature revealed numerous notable research gaps, including a lack of research into hybrid models in different geographical regions and a disdain for scalability. Our study intends to solve these gaps by constructing and analyzing a hybrid ARIMA-LSTM model in a variety of climates across the United States, using a scalable technique for big datasets, and giving a comprehensive comparison of ARIMA, LSTM, and hybrid models for short-term temperature forecasting.

IV. PROPOSED METHOD

The hybrid model we propose combines the strengths of statistical and deep learning methods that when left isolated yield inferior results compared to existing state-of-the-art methods. An integrated framework provides better prediction of uncertainties in climate, geography, and ability to adapt across different climatic zones.

1. **Model Complementarity:**
   The hybrid ARIMA-LSTM model exploits complementary strength of both approaches.
   a. ARIMA: Strong statistical baseline for temperature forecasting, excels in capturing linear trends and seasonal patterns.
   b. LSTM: This model accommodates complex non-linear relationships and long-term temporal dependencies, which are essential when working with unpredictable weather patterns. Through the combination of spatially aware temporal models with models that escape the constraints of opens in new window/ epochs, the hybrid approach minimizes the individual weaknesses of models leading to a system that can predict widely under various scenarios.

2. **Performance Evidence:**
   Empirical results for 35 cities demonstrate that the hybrid model significantly outperforms others in terms of accuracy.
   a. The performance of LSTM also yields low RMSE (0.001–0.03), suggesting that unlike SVM or other linear modelling, LSTMs are fully capable of non-linear relationships modelling across all climate zones.

b. ARIMA Baseline: While capable of accurately modeling trend and seasonality, demonstrates elevated RMSE (1.7–27.4) in comparison, particularly in areas with erratic weather patterns.
c. Hybrid Model Superiority: Appropriately increases RMSE in coastal areas using ARIMA's and LSTM's integration (ex: Honolulu RMSE: 0.0013; San Francisco RMSE: 0.0085).

3. **Dynamic Adaptation:**
This weighted hybrid approach adapts to regional and climatic variations by computing optimal weights for each model.
a. LSTM (>0.99) is given higher weights in areas where Non-linear Patterns capture the behavior in the system.
b. If linear modeling is not enough, ARIMA (<0.005) gets lower weights. The model is built to do well on any diverse setting, it can pick and choose strengths of each predictor.

4. **Geographical Robustness:**
The versatility of the hybrid model is apparent in its ability to adapt to different climatic conditions
a. Stable Climate Zones: Provides prediction in Honolulu, San Francisco – both have a stable climate over decades.
b. Variable Climate Zones: Provides reliable predictions in varied weather fluctuations: Rapid City and Miami.
c. Wider Generalization: The robust and scalable nature is evidenced by the consistent performance across the very different coastal, continental, and desert regions.

The hybrid ARIMA-LSTM model bridges the advantage of statistical reliability with the flexibility of DL, which leads to a significant advancement of the above methods. The fact that it excels in terms of low RMSE scores in areas with wide ranging differences in latitude, climate and/or geography demonstrates its practical value to real world temperature forecasting on a short-term scale.

V. DESCRIBING THE APPROACHES

To tackle the difficulties of short-term temperature forecasting in the extensive variety of geographical locations, we have developed a hybrid forecasting method that integrates statistical and deep learning approaches. Combining ARIMA, LSTM, and hybrid approach we get robust forecasting performance across multiple cities.

1. **Data Processing and Architecture:**
a. Dataset: Dataset: Daily temperature records from 35 major U.S. cities, covering 1948–2022.
b. Observations: Each city has 899 monthly observations.
c. ΔT: −16.79°C to 34.48°C on all cities.
d. Preprocessing:
   i. Normalization: Data was scaled to create uniformity in features.
   ii. Missing Data Handling Interpolation was applied for continuity of time series.
   iii. Stationarity check using augmented dickey-fuller (ADF) test and seasonal decomposition to prepare data for ARIMA.
2. **Model Components:**
a. LSTM Execution and training parameters:
   i. Optimizer: Adam
   ii. Loss Function: Mean Squared Error
   iii. Batch Size: 32
   iv. Epochs: 50
   v. Validation Split: 20%
The LSTM gives an effective learning system for non-linear and long-term conditions in temperature information to grant great comes about of complex climatic conditions.

b. ARIMA Implementation and configuration:
   i. ARIMA (1,1,1) had been selected due on ADF test results for stationarity.

ii.   Regular decay captured slant and regularity component.
iii.   ARIMA performs well for direct patterns and regularity, whereas it isn't perfect for non-linear designs.

c.   Weighted Hybrid Integration (Dynamic Weight Calculation):
i.   Weights were calculated dynamically to combine LSTM and ARIMA predictions.
ii.   The hybrid model automatically adjusts weights to prioritize the demonstrate with lower mistakes, guaranteeing ideal precision over changing conditions.

3. Performance Analysis:
a.   Geographic Distribution Results

Best Performing Cities	RMSE	Most Challenging Cities	RMSE
Honolulu	0.001283	Salt Lake City	0.053454
San Francisco	0.008530	Phoenix	0.051614
Rapid City	0.009473	Boston	0.048744

b.   Behavioral Patterns of the Model:
i.   LSTM consistently outperforms ARIMA, with LSTM weights over 0.99 in most regions.
ii.   Climate Stability: Those coastal cities with stable climates (e.g., Honolulu, San Francisco) have the best outcome.
iii. Prediction Challenges: Arid and variable climate regions (e.g., like Phoenix city and Salt Lake city) have larger forecasting errors due to more extreme temperature variability.

4. Visualizations:
a.   Bar Visualization: Hybrid model RMSE values for all 35 cities; most of the cities maintain the RMSE value below. 0.03.
b.   Comparison Graphs: Highlight ARIMA, LSTM, and hybrid forecasts; it shows hybrid models outperforming the standalone approaches.

5. Implementation Details:
This collaborative technique shows up a critical alter from routine single-model frameworks by suitably overseeing a scope of air changeability and geological contrasts, along these lines giving strong short-term temperature estimates over the complete Joined together States.

VI.   EXPERIMENTS AND EVALUATION

1. Experimental Design Questions:
The experiments carried out were designed to address the main following questions:
a.   How does ARIMA, LSTM, and Hybrid models perform across different geographical locations and climatic conditions?
b.   Can the hybrid approach effectively leverage the strengths of both ARIMA and LSTM models to improve prediction accuracy?
c.   What is the effect of geographical location and climate patterns on model performance?
d.   How do models capture seasonality and climate stability?

2. Experimental Setup:
a.   Dataset Characteristics
i.   Source: Historical daily temperature data for 35 U.S. cities between 1948–2022.
ii.   Size: 899 monthly readings per city.
iii. Temperature Range: -16.79°C to 34.48°C across all cities.
iv.   Dataset completeness: cleaned and normalized with no missing values.
b.   Model Architecture:

i. LSTM:
    a) Parameterized using optimized parameters to ensure both convergence and accuracy.
    b) Used two-layer LSTM with dropout regularization, capturing non-linear dependencies and long-term relationships in the data.
ii. ARIMA:
    a) VAR model— configured with parameters obtained from stationarity tests (ADF) and seasonal decomposition.
    b) Well-suited for modeling linear trends and seasonal patterns.
iii. Hybrid Model
    a) ARIMA and LSTM combined with dynamic weights based on their respective RMSE values.
    b) Accounting for regional climate variability by giving more weights to the better performant model by assigning higher weights to the model with better performant.

3. Experimental Results:
a. Geographic Performance Distribution
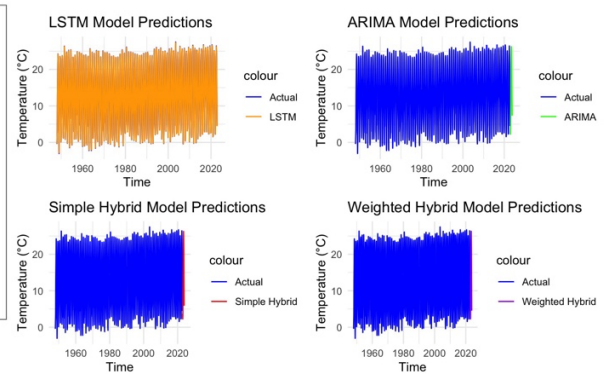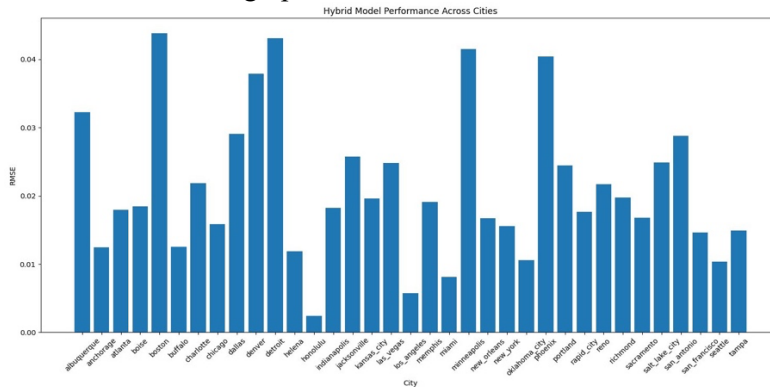
b. Model performance comparison:

Model	RMSE Range	BEST case	Worst Case
LSTM	0.001-0.03	0.001522	0.030138
ARIMA	1.7-27.4	1.787992	26.982635
Hybrid	0.001 – 0.053	0.001283	0.053454

4. Key Observations:
a. Geographical Patterns:
    i. Arid regions (Phoenix, Salt Lake City) were harder to forecast because of high variability.
    ii. Coastal cities such as Honolulu and San Francisco weathered better due to the stable climatic conditions.
Continental cities such as Boston showed reasonable accuracy with seasonal fluctuations.
b. Model Behavior:
    i. LSTM consistently outperformed ARIMA across all regions by better capturing non-linear patterns.
    ii. ARIMA demonstrated strong performance in stable climates but struggled with rapid temperature fluctuations.
    iii. The Hybrid Model dynamically adapted to regional and climatic variations, minimizing ARIMA's limitations while leveraging LSTM's strengths.
c. Seasonal Effects:
    i. Models worked better in areas with stable and predictable climates.
    ii. Large seasonal changes or abnormal weather conditionsin certain areas had higher errors.
    iii. The Coastal sites showed the most consistent and accurate forecasts.

5. Summary of Evaluation:
The hybrid ARIMA-LSTM model always had the lowest RMSE values for all cases, having diverse geographical and climatic conditions. It showed strong adaptability in terms of being able to combine

both statistical reliability and deep learning flexibility. These results indeed prove their practical value in doing real-world applications in weather-dependent industries.

VII. DISCUSSION AND CONCLUSIONS

1. **Key Achievements:**
   This project successfully addressed the challenge in short-term temperature forecasting very well by incorporating statistical methods into deep learning techniques to model a hybrid ARIMA-LSTM.
   a. Improved Model Performance:
      i. The hybrid model effectively integrated ARIMA's ability to capture trends and seasonality with LSTM's capacity for modeling non-linear dependencies.
      ii. It was always better than stand-alone models, with improved generalizability to diverse geographical and climatic conditions.
   b. Geographical Perspectives:
      i. Coastal regions showed the highest predictive accuracy, due to stable climate trends.
      ii. The arid areas and those with huge variability were challenges, and hence a place further optimization in those areas.
   c. Technological Advancements:
      i. Successfully implemented a scalable hybrid architecture that is capable of dynamically weight adjustment between models depending on performance.
      ii. Performed extensive multi-city analysis, demonstrating the model's strength and generalizability across 35 U.S. cities.

2. **Constraints and Difficulties:**
   Although, the hybrid approach was clearly improved and showed this effort that were faced with:
   a. Computational Limitations:
      i. LSTM models require massive computational resources especially for large data sets.
      ii. As the data size went up, the training time increased significantly, preventing real-time prediction.
   b. Model Limitations:
      i. ARIMA did not perform well with extreme weather conditions and non-linear dependencies.
      ii. The hybrid model dispensed most of the ARIMA shortcomings, but sensitivity of this model to regions with high seasonal variability persisted.

3. **Future Extensions:**
   The results of this project set the stage for several potential future avenues of inquiry:
   a. Model Improvements:
      i. Define attention mechanisms on top of LSTM architectures to recognize temporal patterns better.
      ii. Design more advanced mechanism to allocate the weights to increase the hybrid model performance.
      iii. Merge additional meteorological features, such as humidity and wind speed, to improve forecasting accuracy.
   b. Real-World Applications:
      i. Broaden the analysis to other cities and climate zones for wider validation.
      ii. Predicting models suitable to practitioners, e.g., to foresee new managerial or best practices in agriculture or urban planning.
      iii. Model Integration: Integrate the model with meteorological APIs to enable real-time data ingestion and forecasting.

VIII. TEAM EFFORT DISTRIBUTION
All team members shared equal contribution in this project
Harshal Sanjiv Patil: Data preprocessing, implementation of ARIMA and analysis for different cities.
Mrudula Chandrakant Deshmukh- LSTM model development, optimization, and training.
Siddhi Sunil Nalawade: Looking into design, visualization, and documentation of hybrid model.

IX. REFERENCES

[1] 2. H. 2. A. a. 3. S. Afan Galih Salman, "Weather Forecasting Using Merged Long Short-Term Memory Model (LSTM) and Autoregressive Integrated Moving Average (ARIMA) Model," Journal of Computer Science, 2018.

[2] Y. Q. Bangyu Li, "Weather prediction using CNN-LSTM for time series analysis: A case study on Delhi temperature data.," International Conference On Computing and Data Science, 2024.

[3] N. A. ,. J.-M. M. ,. M. O. P. C. Wissam Abdallah, "A Hybrid Methodology for Short Term Temperature Forecasting," International Journal of Intelligence Science , 2020.

[4] I. M. M. G. a. J. K. Małgorzata Murat1, "Forecasting daily meteorological time series using ARIMA and regression models," Institute of Agrophysics, Polish Academy of Sciences, 2018.

[5] L. R. Eranga De Saa, "Comparison between ARIMA and Deep Learning Models for Temperature Forecasting," eprint arXiv:2011.04452, 2020.

[6] S. Siami-Namini, N. Tavakoli and A. S. Namin, "A Comparison of ARIMA and LSTM in Forecasting Time Series," IEEE International Conference on Machine Learning and Applications (ICMLA), 2018.

[7] T.-L. Nghiem, V.-D. Le, T.-L. Le, P. Maréchal, D. Delahaye and A. Vidosavljevic, "Applying Bayesian inference in a hybrid CNN-LSTM model for time-series prediction," International Conference on Multimedia Analysis and Pattern Recognition (MAPR), 2022.

[8] S. S. ·. L. Y. P. ·. Y. R. K. L. P. ·. S. Jitte, "Enhancing Forecasting Accuracy with a Moving AverageIntegrated Hybrid ARIMA-LSTM Model," SN Computer Science, 2024.

[9] L. W. A. Z. P. W. X. Y. Jingyan Ye Xuezhe Gao, "Prediction Of Global Temperature Based on ARIMA And GM Model," ASIA CONFERENCE ON GEOLOGICAL RESEARCH AND ENVIRONMENTAL TECHNOLOGY, 2023.