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Research Article

Hyper-Localized Weather Forecasting System

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ABSTRACT

Traditional weather forecasting methods are inconvenient and do not consider detecting weather patterns for remote locations. A hyper-localized Internet of Things (IoT)-based weather forecasting app using artificial intelligence can turn the disadvantage into a strength. This study attempts to overcome the shortcomings of conventional weather forecasting methods by utilizing machine learning models, i.e., Long Short-Term Memory (LSTM) with attention mechanisms, to make precise and timely predictions for a specific location. The system uses real-time information from IoT sensors to enhance the precision of the predictions and detect specific weather patterns. The system includes data acquisition using IoT devices, preprocessing techniques, feature extraction, and model training. The findings confirm the effectiveness of the attention-based LSTM model in predicting various weather parameters, of which temperature and sea level pressure obtained the maximum accuracy.

Keywords: Hyper-localized weather forecasting, Artificial Intelligence, Internet of Things (IoT), Long Short-Term Memory (LSTM) networks, Attention mechanisms, Machine learning algorithms.

1. INTRODUCTION

Weather has a significant impact on people's daily lives. It has a very significant role in society's socio-economic life. Historically, weather forecasting has depended on using sophisticated mathematical and computer models of atmospheric processes based on data obtained at weather stations, satellites, and other sources. Although these have become increasingly accurate, they lag when predicting weather in distant and small areas. Due to this, other, more localized, and less sophisticated methods based on machine learning are being explored, as they can potentially make more accurate and timely predictions [1]. Improvements in machine learning, i.e., deep learning techniques such as LSTMs, have proven beneficial in weather forecasting. The techniques can learn sophisticated patterns and associations in historical weather data and issue better forecasts [2]. Compared to traditional techniques, ML techniques can learn new patterns easily and fuse data from broader sources, such as real-time sensor data from IoT sensors [3].

This method provides much more accurate outcomes in the local geographical environment, and the forecast can be made specifically to consider local microclimates and topography, which can be a primary factor in the climate. Such specificness can be helpful in agriculture and city planning and can help make the public aware of localized unforeseen weather conditions. Artificial intelligence and IoT make the utilization of the hyper-localized weather forecasting system easier. AI algorithms can process large amounts of data, identifying patterns and correlations [9]. Weather forecasts become more specific and detailed, especially if the weather is highly complex. IoT, however, provides a dense set of measurements of the current weather, and it is possible to make more accurate predictions that are more localized.

This work integrates the most advanced technology to develop a more effective weather forecasting solution. It uses an LSTM model with an attention mechanism to leverage the past data appropriately and appropriately weigh the most significant features. It also defeats the disadvantage of most of the conventional forecasting methods. The 24-hour forecast horizon offers a trade-off between providing actionable information and accuracy, as long-term forecasts are not as accurate [4]. The solution is also optimized using real-time IoT sensor data, which helps the model detect the current conditions and short-term trends in a hyper-local area.

2. LITERATURE REVIEW

The "Numerical Weather Prediction" written by Baer presents an overview of numerical weather prediction throughout the past forty years and its present operational barriers. Baer (2000) [5] states that powerful computers have enabled feasible progress through complex simulations and fast data analysis capabilities [5]. Data processing times have shortened due to methods that extract additional knowledge from currently available data. Baer (2000) [5] mentions both the barriers and challenges to this system. Numerical weather prediction functions within established limits because available computing capabilities remain a significant constraint. Atmospheric process complexities and necessary approximations of governing equation solutions result in prediction uncertainties that cannot be avoided. NWP system documentation preceded "Enhancing climate forecasting with AI: Current state and prospect" to gain an idea regarding AI applications used for climate forecasting. The paper confirms that artificial neural networks and deep learning-based machine learning approaches have shown their effectiveness in making early warning systems' weather forecasting more accurate based on [6]. AI improves climate forecasting by studying big data databases and finding complex patterns based on published work [6].

We delved into the "End-to-end data-driven weather prediction" described in Allen et al. [7] because of their Aardvark Weather end-to-end machine learning model that replaces all functions of Numerical Weather Prediction (NWP) pipelines. The model achieves performance levels similar to standard operational NWP frameworks at a reduced cost and increased speed, according to research done by [7]. Aardvark Weather achieves its main success through its modular design structure that includes state estimation through an encoder and autoregressive forecasting computation with either specific operation decoding or local prediction decoding [7]. Aardvark is an adaptable model since its tuning system enables it to operate with varying variables and positions. Utilizing such parts places weather forecasting systems on a level with independent units that operate and are highly adaptable.

Choosing a model is critical for good prediction. We reviewed "Attention Is All You Need," which describes the Transformer, a new and simple network architecture for sequence transduction models. Vaswani et al. [8] propose an architecture composed entirely of attention mechanisms, discarding convolutions and recursions. In experiments on standard machine translation tasks, transformer models produced higher quality, improved parallelization, and much lower training time than existing models [8]. Furthermore, attention models effectively model long-term dependencies, unlike recurrent or convolutional networks, because the path length between positions in a sequence is always constant. Vaswani et al. [8] show that the parallelizable design of the Transformer reduces training time to just 3.5 days on 8 GPUS and outperforms existing models in both accuracy and computational efficiency.

With the help of "Integration of IoT- AI-powered local weather forecasting: A Game-Changer for Agriculture," I Understood IOT integration with AI for hyperlocal weather forecasting. Suman Kumar Das, Pujyasmita Nayak. [3] investigate the possible use of AI-powered, IoT-based solutions to provide real-time, high-resolution meteorological data for agricultural decision-making and increased farm output. Suman Kumar Das, Pujyasmita Nayak. [3] their primary findings include establishing a comprehensive framework that uses IoT and machine learning to improve local weather forecasts for climate-resilient agriculture.

3. METHODOLOGY

The fundamental technique for weather forecasting using artificial intelligence entails gathering a dataset of weather patterns like temperature, precipitation probability, humidity, sea level pressure, and time of weather pattern occurrence. After data collection, forecasting can be performed using an attention-based LSTM algorithm.

3.1. Data Collection:

The quality of training data has a direct impact on the forecasting quality of a time series analysis model. Since time series analysis and attention-based LSTM demand extensive data, the dataset includes data from the beginning of January 2024. It is updated hourly using an IOT device. The Raindrop Module, the Barometric Pressure Sensor

(BMP180), and the Temperature and Humidity Sensor (DHT 11) are the IOT sensors that are utilized to gather weather data [10][11]. These sensors collect data, which is then saved in JSON and stored in Firebase.

An overview of the dataset:

{

“Temperature”: 29.3,

“Humidity”: 61,

“Pressure”: 1016.84,

“Rainfall”: “No Rain,”

“Timestamp”: “2025-02-12 16:00:00”

}

3.2. Data Preprocessing:

3.2.1. Generating the Dataset

An IoT-based data collection device is built to create a highly targeted weather forecasting system. There are three main sensors in the system:

- DHT11 sensor: Measures temperature and humidity [12].
- BMP180 sensor: Measures the pressure.
- Rain Sensor: Calculates the probability of precipitation.

The IoT devices were configured to capture weather patterns and features at hourly intervals. The captured data was sent to a cloud-based Firebase server for preparation and analysis.

3.2.2. Balancing the Dataset

In order to improve the model's quality, the gathered data was preprocessed. The crucial preprocessing action was managing missing values to preserve data continuity. Data Normalization to enhance model performance and stability, sensor readings were scaled using Min-Max scaling to a range of 0 and 1. Using a moving average filter to reduce noise. Time-series formatting was organized into time-windowed sequences to prepare the data for attention-based LSTM model training.

3.2.3. Feature Extraction

An essential preprocessing component was extracting meaningful features to improve forecasting accuracy. Among the derived features, the dew point was calculated using the temperature and relative humidity values captured by the DHT11 sensor. The value of the dew point is calculated by [13]:

Dew = Temperature - [(100 - Relative Humidity)/5]

The dew point feature provides critical insights vital for weather phenomena such as fog, frost, and precipitation. Dew point as a feature also enhances the model's ability to learn complex weather patterns and improves its capability. Effective feature extraction ensures that the forecasting model provides an important and more informative dataset, improving the accuracy and reliability of weather predictions.

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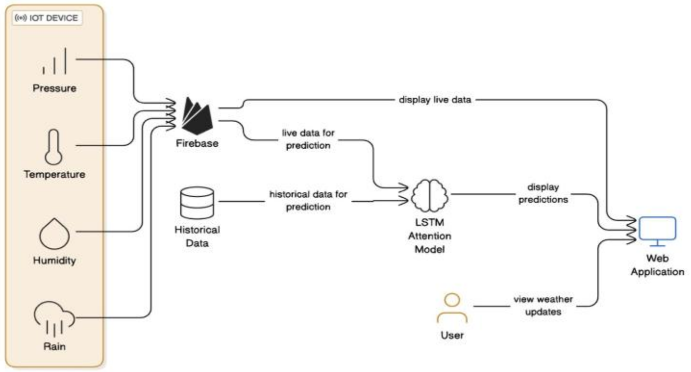

Fig. 1. Framework for hyper-localized weather forecasting

3.3. Model Selection:

Choosing the right model is crucial for building an efficient system; it should accurately represent the data collected. Based on experimentation with several models, including SVMs (support vector machines), Random Forests, and LSTMs (long short-term memory) [14]. Given the type of data collected, LSTM (time-series-based) performed the best and caused the least problems during the training of the models.

In order to predict the future, LSTMs are particularly good at remembering past information. Essentially, past weather data is used to predict future data. LSTMs better identify important temporal features, such as high afternoon and cooler evening temperatures. It also aids in multi-step prediction, such as forecasting for a few hours to a few days or months.

Additionally, an attention mechanism is employed to enhance the performance of the LSTM predictions. This mechanism's function is to assign weights to only significant time steps or predictions that are received from the LSTM layer [8]. The attention layer determines which weather predictions are the most crucial or significant, such as the prediction made two hours prior, which is more significant than the prediction made ten hours prior. Hence, the attention mechanism gives these time-steps more weight.

3.4. Feature Engineering:

Having features like temperature, humidity, precipitation, sea level pressure and dew majorly performs well for weather forecasting, but mapping or relating these features to one another frequently causes problems with time series models. In order to map features that are crucial for forecasting, we have added features like hour_sin, hour_cos, day_of_year_sin, and day_of_year_cos[15]. By assuming that the hours (0 to 23) appear to be far apart in a straight line, we are actually bringing them closer together when we consider cyclic encoding. Both sin and cos are being used. Since they work together to map the key features, utilizing just one will cause information to be lost. The formula is given as:

For Hours:

hour_sin = sin(2π * hour / 24)

hour_cos = cos(2π * hour / 24)

For Day of year:

day_of_year_sin = sin(2π * doy / 365)

day_of_year_cos = cos(2π * doy / 365)

Since the weather is frequently cyclical, using cyclical elements is beneficial. The hour-sin and hour-cos are used to determine daily essential trends, such as afternoon temperature peaks and evening temperature cools, while the day-of-year-sin and day-of-year-cos are used to map seasonal trends, such as summer and winter.

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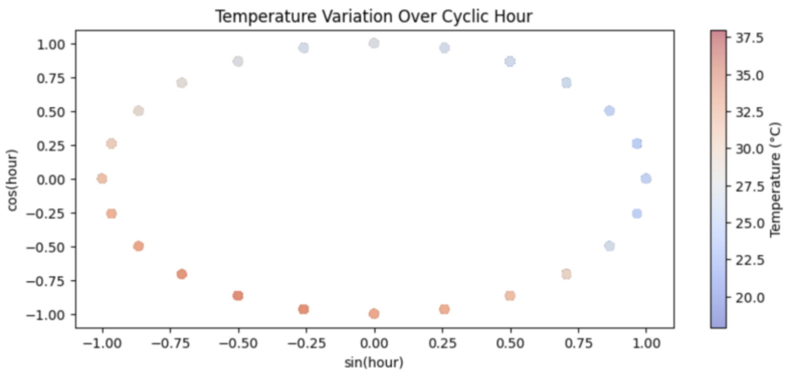

Fig. 2. Mapping cyclical hour with variation in temperature

3.5. Model Training:

As part of the model training, we tried multiple approaches, such as training a multi-level model that predicts all the features simultaneously, such as temperature, pressure, humidity, precipitation, and dew [16]. However, we did not get the desired accuracy, and the correlation between some features was high, causing the model to perform poorly.

Thus, we used separate models for temperature, humidity, pressure, dew, and other variables to train a "single target multi-step LSTM with attention model" [15]. Beginning with the model's X and Y variables (train and test data). Temperature is the target y, and all other features are X. This process is repeated for all other target features. Other features like dew, humidity, and temperature were added to the feature and used as the X feature to predict the dew as the output feature for better accuracy.

Regarding the specific model, LSTM operates by adding two components: (forcast_horizon = 24), which aids in predicting the hourly temperature for the upcoming 24 hours, and (sequence_window = 48), which determines how much historical data to view in order to produce the final prediction.

As a result, the phrase "Single target multi-step LSTM with Attention model" refers to the fact that we have a model that can predict each weather feature separately, or "Single-target," and that we are utilizing the LSTM algorithm with an Attention layer to do so for the next 24 hours.

4. RESULTS AND DISCUSSION

Through this study, we evaluated the performance of attention-based LSTM on the weather data collected by an IoT device for a hyper-localized region. The model was trained separately for every feature to provide more accurate results. We used RMSE (root mean square error) and RAE (relative absolute error) as performance metrics to check the prediction accuracy for each feature collected by the device.

Table 1. Model Result with RMSE and RAE

Weather Features	RMSE	RAE
Temperature	2.0670	1.7370
Pressure	2.6134	2.1501
Humidity	12.0829	9.4203
Rainfall	3.1229	2.9321
Dew	3.4229	2.6321

The study revealed that the error value for temperature prediction was the lowest, with an RMSE of 2.0670 and an MAE of 1.7370, demonstrating that the model was most efficient in forecasting temperature. The value for the temperature prediction also closely follows the actual temperature for a 24-hour time window.

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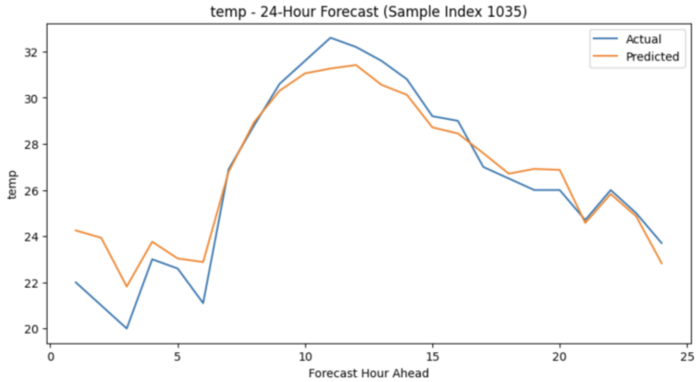

Fig. 3. Actual vs Predicted temperature value

Similarly, the error value for pressure also closely resembles that of temperature. An RMSE of 2.6134 and an MAE of 1.7370 demonstrate the model's proficiency with the pressure feature—mapping the predicted value with the actual value being loosely bound as compared to temperature.

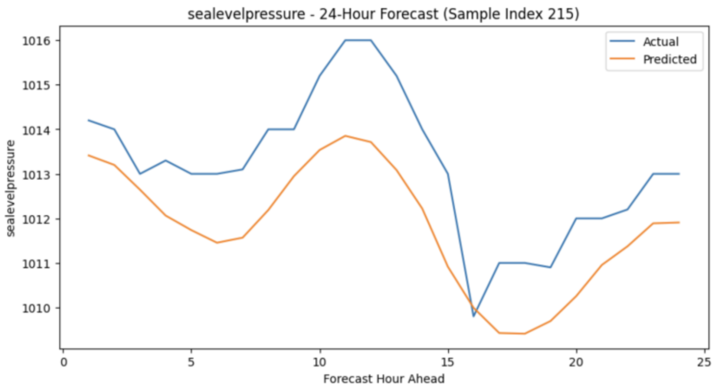

Fig. 4. Actual vs predicted pressure value

On the other hand, predictions for dew had a slightly higher error rate, with the MAE of 2.6321 and the RMSE of 3.4229. This shows that the model had more trouble capturing details of dew behavior but was still within an acceptable range. This could be due to the dependent behavior of dew on temperature and humidity.

Humidity had the most error of all the features, with the RMSE of 12.0829 and the MAE of 9.4203. This means that the humidity value is uncertain and harder to predict since it is dynamic and closely correlates with temperature and dew point. The results indicate that while the AI model performs well in predicting weather patterns concerning temperature and pressure, more effort is needed for features such as humidity.

5. CONCLUSION

This research work studied hyper-localized weather forecasting systems using Artificial Intelligence and IoT devices. It shows how traditional weather forecasting methods differ from the new promising AI-related forecasting and the possibility of remote region weather predictions with faster results. The attention-based LSTM model shows high-performance levels across different weather features, with temperature and sea pressure showing the highest accuracy. However, various challenges remain in predicting more dynamic features like humidity. Adding IoT sensors for real-time data collection and creating features like dew have proven effective in enhancing the model's forecasting capabilities. More work is needed to improve the model's performance for dynamic weather patterns and explore additional sensors for the IoT device to improve forecast accuracy. This study contributes to AI-powered weather forecasting and provides potential benefits for various fields that rely on accurate weather forecasting to make decisions.

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