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Deep Neural Network-Based Air Temperature Prediction Using Temporal and Spatial Feature Learning

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Abstract: Accurate short-term air temperature prediction plays a vital role in agricultural planning, environmental monitoring, and smart climate management systems. Traditional forecasting approaches often struggle to capture nonlinear temporal variations and dynamic weather patterns, resulting in reduced prediction accuracy and inefficient resource utilization. To address these limitations, this paper presents a hybrid deep learning framework for short-term air temperature prediction using Feed Forward Neural Network (FFNN), Long Short-Term Memory (LSTM), and two-dimensional Convolutional Neural Network (CNN2D) models. The proposed system utilizes historical temperature datasets along with temporal attributes such as day, month, year, and time for forecasting future temperature values. Initially, data preprocessing techniques including normalization, feature extraction, and train-test splitting are performed to improve model learning efficiency. FFNN is employed for baseline prediction, while LSTM captures sequential temporal dependencies in time-series data. Furthermore, CNN2D is integrated to enhance feature extraction capability and reduce prediction error through parameter sharing and efficient learning. The trained models are deployed using a Flask-based web application that enables real-time temperature prediction through a user-friendly interface. Experimental evaluation demonstrates that the proposed CNN2D-enhanced framework achieves superior prediction accuracy with reduced Mean Absolute Error (MAE) and improved forecasting reliability compared to conventional neural network approaches. The proposed system provides an efficient, scalable, and practical solution for real-time agricultural and environmental temperature forecasting applications.

Index terms - *Air Temperature Prediction, Deep Learning, Feed Forward Neural Network (FFNN), Long Short-Term Memory (LSTM), CNN2D, Time-Series Forecasting, Artificial Neural Networks, Real-Time Prediction, Agricultural Forecasting, Climate Monitoring, Flask Web Application, Machine Learning, Temperature Forecasting, Smart Agriculture.*

1. INTRODUCTION

Air temperature prediction plays a significant role in agriculture, environmental monitoring, climate analysis, and smart resource management systems. Accurate short-term temperature forecasting helps farmers, agricultural industries, and environmental agencies make effective decisions related to irrigation scheduling, greenhouse management, crop protection, storage systems, and energy optimization. Sudden fluctuations in temperature can negatively affect crop growth, reduce agricultural productivity, and increase operational costs. Therefore, developing intelligent forecasting systems capable of predicting future temperature conditions with high accuracy has become an important research area in recent years.

Traditional temperature forecasting methods mainly depend on statistical models and basic machine learning techniques such as linear regression and decision trees. Although these methods provide acceptable performance for simple datasets, they often fail to capture complex nonlinear relationships and temporal dependencies present in meteorological time-series data. Weather conditions continuously

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change over time, making temperature prediction a highly dynamic problem that requires more advanced computational approaches. In addition, conventional forecasting systems usually rely on multiple meteorological parameters and high computational resources, which limit their practical implementation in real-time agricultural environments and resource-constrained systems.

Recent advancements in artificial intelligence and deep learning have significantly improved the performance of time-series forecasting applications. Deep learning models such as Feed Forward Neural Networks (FFNN), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN) are capable of automatically learning hidden patterns and temporal relationships from large-scale datasets. FFNN models provide efficient nonlinear mapping between historical and future temperature values, while LSTM networks effectively handle sequential dependencies and long-term temporal variations in time-series data. Furthermore, CNN-based architectures improve feature extraction capability through parameter sharing and local pattern learning, leading to enhanced prediction accuracy and reduced overfitting problems.

In this work, a hybrid deep learning framework for short-term air temperature prediction is proposed using FFNN, LSTM, and CNN2D models. The system utilizes historical hourly temperature datasets along with temporal attributes such as day, month, year, hour, and minute to forecast future air temperature values. Initially, preprocessing operations including normalization, feature extraction, and train-test splitting are performed to improve model learning efficiency and prediction stability. FFNN is employed as a baseline forecasting model, whereas LSTM captures temporal dependencies in sequential weather data. Additionally, CNN2D is integrated to enhance spatial feature learning and improve overall forecasting performance.

The proposed system is deployed using a Flask-based web application that enables real-time air temperature prediction through a simple and interactive interface. Users can upload test datasets and obtain immediate forecasting results for future temperature conditions. Experimental results demonstrate that the CNN2D-enhanced framework achieves lower prediction error and better forecasting reliability compared to conventional neural network approaches. The developed system provides an efficient, scalable, and practical solution for real-time temperature forecasting in smart agriculture and environmental monitoring applications.

2. LITERATURE SURVEY

1. Enhanced hourly temperature prediction using advanced ensemble neural networks for energy system efficiency optimization in hyper-arid regions:

In order to increase prediction accuracy, this research proposes sophisticated methods for air temperature forecasting based on the link between meteorological data and feedforward neural network models. With a root mean square error (RMSE) of 1.5587 and all correlation coefficients above 0.97 during the test phase, an ideal single neural network model was created and optimized by dataset segmentation, yielding great predictive performance. Furthermore, robust results were obtained by implementing a bootstrap-aggregated neural network (BANN) model with 30 networks in a stacked ensemble; both validation and testing correlation coefficients were near the optimal value. Sensitivity analysis also showed that wind speed, extraterrestrial radiation, and actual solar time were the most significant predictors, which is in line with their physical significance to temperature change. Additionally, the model's validity was verified by employing the Williams plot for applicability domain analysis, which revealed that more than 97% of the predictions were within allowable error bounds. The BANN model's promise for precise air temperature forecasting under a variety of meteorological situations was reinforced by a comparative evaluation against other existing models, which showed the higher predictive performance of the suggested technique.

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2. Sensitivity analysis of physical regularization in physics-informed neural networks (PINNs) of building thermal modeling:

Buildings account for more than 40% of all primary energy use, and they are crucial to the energy transition and carbon neutrality. An accurate control-oriented thermal model is essential for energy management and efficiency in order to fully realize their potential. However, because physics-informed models are complicated and time-consuming, and because solely data-driven models have issues with generalization and interpretability, creating such a model is still a difficult undertaking. Therefore, we suggest a Physics-informed Neural Network (PINNs) model based on a fully connected neural network architecture and a simplified Resistance-Capacitance (2R2C) thermal model. We propose and examine three factors: prediction durations, data lengths, and physical regularization requirements. Initially, a real case building's historical data is used to estimate the parameters in the 2R2C thermal model. Second, by recreating the restricted loss function, the 2R2C model is included into a fully connected neural network. Lastly, physics-informed conditional regularization is used to examine how well the suggested PINNs model predicts temperature and load demand in relation to various data lengths and prediction periods. In multi-step predictions in buildings, the PINNs model (temperature CVRMSE of 4.31% and RMSE of 0.94 °C) performs better than the physic-based grey-box 2R2C model (temperature CVRMSE of 8.76% and RMSE of 1.91 °C) and pure neural networks (NNs) (temperature CVRMSE of 5.91% and RMSE of 1.27 °C). The findings also highlight how crucial it is to include physical knowledge into traditional data-driven models. Because of its simplicity and universality, the suggested PINNs model may be easily and effectively used in building energy management systems.

3. Machine Learning-Based Temperature Forecasting for Sustainable Climate Change Adaptation and Mitigation:

In order to help with sustainable environmental planning and solutions for climate change adaptation, artificial neural networks (ANN) and machine learning models (linear model, support vector machine, K-nearest neighbor, random forest) were used in this study to estimate temperature. The study examined monthly temperature, precipitation, wind speed, and humidity data for the province of Istanbul between 1950 and 2023. The ANN model produced estimates with 96% accuracy, whereas the random forest (RF) model outperformed the other machine learning models. The k-fold cross-validation procedure improved the models' capacity for generalization. Temperature was shown to be inversely correlated with input factors (humidity, wind, and precipitation). According to the current findings, temperature estimate and sustainable climate monitoring can benefit from the employment of artificial intelligence and machine learning approaches. Through a few trustworthy approaches for assessing climate change, designing sustainable energy, and creating strategies for agricultural adaptation, this study meets sustainability goals. The approach may be applied to various regional climate assessments and might support evidence-based decision-making for climate resilience and sustainable development.

4. Development of a neural network model for an automated HVAC system based on collected data:

Ventilation and air conditioning systems are the subject of the study as they serve as the source of data for the creation of a neural network model based on them. In order to streamline the model building process, the primary focus is on the method selection and data collecting for training a neural network model based on the MATLAB software package. The study's primary concern was the difficulty of creating mathematical models for air conditioning and ventilation systems. The development and practical use of traditional methodologies are complicated by the substantial computational resources and in-depth physical process understanding they demand. The study's findings demonstrate one method for employing neural networks to model ventilation and air conditioning systems. The suggested method

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makes it possible to quickly train the model using actual data, which will enable future research to increase the system's performance and adapt it to changing operating conditions. In contrast to standard mathematical models, which need the exact description of all relationships and parameters, the produced conclusions may be explained. Complex nonlinear functions can be approximated by neural networks without requiring a thorough comprehension of physical processes. As long as there is enough data to train the neural network, the suggested method may be used to air conditioning and ventilation systems. Integrating such a system with controllers and SCADA systems that offer operational parameter collecting from the environment is also crucial. Neural network models are particularly useful in energy-saving systems, smart buildings, and industrial facilities where it's critical to maximize energy utilization while ensuring user comfort. These models may also be used in cloud systems to regulate climate parameters centrally across several buildings or industry complexes.

5. Innovative machine learning approaches for indoor air temperature forecasting in smart infrastructure:

In the modern world, maintaining an ideal interior environment in buildings and managing energy efficiently are essential jobs. Using cutting-edge machine learning techniques, this research proposes a novel surrogate modeling strategy for forecasting indoor air temperature (IAT) in buildings. The use of Long Short-Term Memory (LSTM) networks for time-series modeling, which greatly improves the capture of temporal dependencies in temperature forecasts, is at the heart of this work. The proposed LSTM with RWCV (Rolling Window Cross-Validation) offers significant advantages over a usual LSTM in time-series tasks, particularly due to its ability to adapt to new data trends through the rolling window mechanism. It enhances model assessment with temporal integrity, avoids overfitting by dropout and cross-validation, and produces more reliable and broadly applicable forecasts in dynamic contexts. Traditional LSTM models, on the other hand, might not be able to handle dynamic time-series data well and are more appropriate for static, non-evolving datasets. A thorough assessment framework including measures like mean square error (MSE) and the coefficient of determination (R2) is created in order to thoroughly evaluate model performance. Furthermore, a new technique for cumulative error analysis is presented that allows for real-time monitoring and model modification to sustain forecast accuracy over time. The model's robust generalization capabilities are demonstrated by test results, which show that model losses on the test dataset are only slightly larger than those on the training dataset. Depending on how the facility is operated, loss numbers can range from 0.0004709 to 0.02819861. Adaboost and Gradient Boosting models beat linear regression, according to a comparison investigation, underscoring their potential for attaining pleasant and energy-efficient interior climate control in buildings. The results highlight the effectiveness of the suggested method for IAT prediction and provide areas for further study in dataset growth and model optimization to improve building energy saving and climate control.

3. METHODOLOGY

i) Proposed Work:

The proposed work introduces a hybrid deep learning framework for short-term air temperature prediction using Feed Forward Neural Network (FFNN), Long Short-Term Memory (LSTM), and CNN2D models. The system utilizes historical temperature datasets along with temporal attributes such as day, month, year, hour, and minute to forecast future temperature values accurately. Initially, preprocessing techniques including normalization, feature extraction, and train-test splitting are performed to improve model learning efficiency and prediction stability. FFNN is employed for baseline nonlinear prediction, while LSTM captures sequential dependencies and temporal patterns present in time-series weather data.

To further enhance forecasting performance, a CNN2D architecture is integrated for advanced feature extraction and reduced computational

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complexity through parameter sharing. The hybrid framework improves prediction accuracy, minimizes overfitting, and supports reliable real-time forecasting for agricultural and environmental applications. The trained models are deployed using a Flask-based web application that enables users to upload test data and obtain immediate temperature predictions through an interactive interface. Experimental analysis demonstrates that the CNN2D-enhanced framework achieves lower prediction error and superior forecasting performance compared to traditional neural network methods.

ii) System Architecture:

The system architecture for the proposed air temperature prediction framework is designed to process historical temperature data and generate accurate short-term forecasts using deep learning techniques. Initially, the system accepts air temperature data collected from historical meteorological records. This raw dataset contains temporal information such as date, time, and temperature values. The collected data is then forwarded to the data preprocessing stage, where operations such as cleaning, normalization, feature extraction, and formatting are performed. These preprocessing steps improve data quality and prepare structured inputs suitable for efficient neural network training and prediction.

After preprocessing, the processed dataset is provided to the CNN2D-based model training module, which acts as the core prediction engine of the system. The CNN2D architecture performs feature extraction and learns hidden spatial-temporal patterns from the temperature dataset using convolution operations and parameter-sharing mechanisms. The trained model generates predicted air temperature values with improved forecasting accuracy and reduced prediction error. Finally, the predicted results are displayed to the user through the forecasting interface, enabling real-time temperature prediction for agricultural management, environmental monitoring, and smart climate control applications.

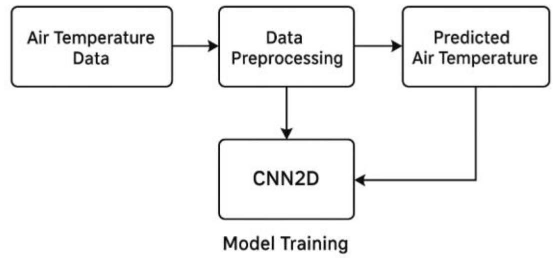

Fig.1. Proposed Architecture

iii) MODULES:

1. Importing the Packages

This module loads all essential Python libraries required for data handling, preprocessing, visualization, and deep learning model development. It initializes libraries such as NumPy, Pandas, Matplotlib, Scikit-learn, TensorFlow, and Flask to ensure smooth execution of numerical computations, plotting operations, and neural network processing throughout the system.

2. Exploring the Dataset

This module reads the historical air temperature dataset and examines its structure to understand available attributes and data patterns. It helps identify missing values, timestamp formats, and temperature variations across different periods, ensuring that the dataset is suitable and properly organized for short-term forecasting tasks.

3. Visualization

This module generates graphical plots and charts to analyze temperature behavior over time. Visualization helps observe seasonal trends, hourly fluctuations, and abnormal temperature changes, providing better insight into dataset characteristics before model training and improving understanding of the forecasting problem.

4. Data Processing

This module prepares raw temperature data for neural network training by extracting important temporal features such as day, month, year, hour, and minute. It converts the data into structured numerical formats suitable for machine learning and organizes input features and target labels required for accurate prediction.

5. Normalizing & Shuffling

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This module normalizes temperature values into a standard range to improve model learning stability and convergence speed. It also shuffles the dataset randomly to eliminate training bias and improve the generalization capability of FFNN, LSTM, and CNN2D models during the training process.

6. Split the Data into Train & Test

This module divides the processed dataset into training and testing sets. The training dataset is used to teach the deep learning models, while the testing dataset evaluates prediction accuracy on unseen data. Proper splitting helps prevent overfitting and ensures reliable model validation.

7. Model Training

This module trains the proposed FFNN, LSTM, and CNN2D models using historical temperature data. FFNN performs nonlinear mapping, LSTM captures sequential temporal dependencies, and CNN2D extracts advanced spatial-temporal features using convolution operations. The training process continuously updates model parameters to improve forecasting accuracy.

8. Evaluation

This module evaluates the prediction performance of all trained models using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 Score. These evaluation metrics help compare model efficiency and identify the best-performing architecture for accurate temperature forecasting.

9. Flask Server

This module deploys the trained prediction model through a lightweight Flask-based web application. It handles communication between the user interface and backend prediction engine, enabling users to upload input data and receive real-time air temperature forecasting results through a browser interface.

10. User Login

This module provides authentication functionality by validating usernames and passwords before allowing access to the prediction system. It restricts unauthorized access and ensures secure usage of the forecasting application and uploaded datasets.

11. Air Temperature Prediction

This module enables users to upload future date-and-time datasets and receive predicted air temperature values instantly. The system processes the uploaded data using the trained deep learning model and displays the forecasting results in a structured and user-friendly format for agricultural and environmental decision-making.

12. Logout

This module securely terminates the active user session after completion of forecasting operations. It clears authentication details, prevents unauthorized reuse of the system, and maintains secure handling of prediction activities within the web application.**iv) ALGORITHMS:**

1. LSTM ANN (Long Short-Term Memory Artificial Neural Network)

LSTM ANN is an advanced recurrent deep learning model designed for processing sequential and time-series data by capturing long-term temporal dependencies through memory cells and gating mechanisms. It effectively overcomes the vanishing gradient problem faced by traditional recurrent networks and learns dynamic patterns from continuously changing datasets. In the proposed system, LSTM analyzes historical air temperature sequences to identify temporal variations and generate accurate short-term temperature forecasts for agricultural and environmental applications.

2. FF ANN (Feed Forward Artificial Neural Network)

Feed Forward Artificial Neural Network (FF ANN) is a basic deep learning architecture where data flows in a single direction from input layer to output layer through hidden layers without feedback connections. It learns nonlinear relationships between input features and target outputs using weighted parameters and activation functions during training. In this project, FF ANN is used as a baseline forecasting model to predict future air temperature values efficiently with lower computational complexity and stable prediction performance.

3. Extension CNN2D (Two-Dimensional Convolutional Neural Network)

Extension CNN2D is an enhanced convolutional deep learning model designed to automatically extract important spatial and temporal features from structured datasets using convolution and parameter-sharing operations. It improves prediction accuracy by learning hidden patterns and reducing overfitting through efficient feature extraction mechanisms. In the proposed framework, CNN2D enhances short-term air temperature forecasting performance by providing reliable, low-error predictions suitable for real-time agricultural and environmental monitoring applications.

4. EXPERIMENTAL RESULTS

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The proposed hybrid deep learning framework was experimentally evaluated using historical air temperature datasets to measure the forecasting performance of LSTM ANN, FF ANN, and Extension CNN2D models. The dataset was divided into training and testing phases to analyze prediction accuracy across different forecasting intervals. Performance evaluation was carried out using Mean Absolute Error (MAE), where lower values indicate better prediction capability. The experimental comparison graph demonstrates that the Extension CNN2D model consistently achieved lower MAE values compared to LSTM ANN and FF ANN during both training and testing phases. In the first four hours of training data, CNN2D obtained an MAE of 0.62, whereas FF ANN and LSTM ANN recorded MAE values of 1.1 and 1.5 respectively. These results indicate that CNN2D provides more accurate learning and better feature extraction capability during model training.

Further evaluation on testing datasets confirmed the superior performance of the proposed CNN2D framework for short-term air temperature forecasting. During the first four hours of testing, CNN2D achieved an MAE value of 1.54, slightly outperforming FF ANN with 1.56 and significantly outperforming LSTM ANN with 2.93. Similarly, for the last four hours of testing data, CNN2D produced the lowest MAE value of 3.33 compared to FF ANN with 4.1 and LSTM ANN with 5.25. The comparison graphs and performance evaluation tables clearly illustrate that the CNN2D-enhanced framework reduces prediction error and improves forecasting reliability through efficient feature learning and parameter sharing. These experimental outcomes demonstrate that the proposed hybrid deep learning system is effective for real-time agricultural and environmental air temperature prediction applications.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

$$Recall = \frac{TP}{(FN + TP)}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

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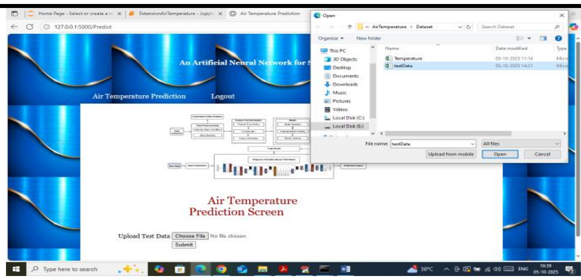

Fig2 Uploading test image

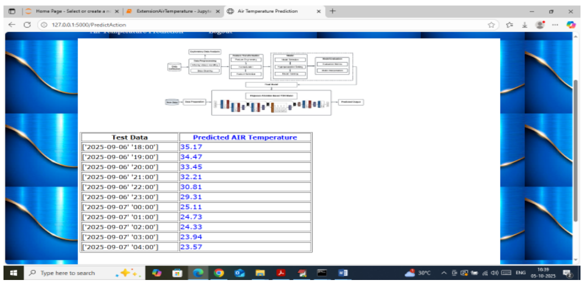

Fig3 Prediction result

5. CONCLUSION

This paper presented a hybrid deep learning framework for short-term air temperature prediction using Feed Forward Artificial Neural Network (FF ANN), Long Short-Term Memory (LSTM), and Extension CNN2D models. The proposed system utilized historical temperature data along with temporal features such as day, month, year, and time to generate accurate forecasting results. Data preprocessing techniques including normalization, feature extraction, and train-test splitting were performed to improve model learning efficiency and prediction stability. The trained models were deployed through a Flask-based web application that enabled real-time temperature prediction using a simple and user-friendly interface.

Experimental evaluation demonstrated that the Extension CNN2D model achieved superior forecasting performance with lower Mean Absolute Error (MAE) values compared to FF ANN and LSTM models across multiple testing intervals. The CNN2D architecture improved feature extraction capability, reduced computational complexity, and minimized prediction error through parameter-sharing mechanisms. The obtained results confirm that the proposed framework provides reliable, scalable, and efficient short-term air temperature forecasting suitable for agricultural management, environmental monitoring, and smart climate control applications. Overall, the developed system offers an effective real-time forecasting solution capable of supporting intelligent decision-making in modern agricultural and environmental systems.

6. FUTURE SCOPE

In the future, the proposed air temperature prediction system can be enhanced by integrating additional meteorological parameters such as humidity, rainfall, wind speed, atmospheric pressure, and solar radiation to improve forecasting accuracy under diverse climatic conditions. Advanced deep learning architectures such as Transformers, GRU, and hybrid attention-based models can also be incorporated for better temporal pattern learning and long-range forecasting. Furthermore, the system can be integrated with IoT sensors and cloud-based platforms to enable real-time environmental monitoring and smart agriculture automation. Mobile application support, edge-device deployment, and large-scale climate prediction capabilities can further improve the practicality, scalability, and real-world usability of the proposed framework.

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