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Advanced Explainable AI Framework for Dew Point Forecasting with Attention-Assisted Temporal Convolutional Networks

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Abstract: ***Forecasting of dew point temperature is an important aspect of monitoring, climate management, agriculture planning, and disaster mitigation. The moisture content of the atmosphere is determined by dew point temperature and it directly affects the weather, human comfort, crop productivity, and energy consumption. Many traditional statistical methods and popular machine learning models are unable to handle the temporal dynamics, seasonal trends and nonlinear relationships in meteorological data. While deep learning models like Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) have shown promising forecasting accuracy, they often suffer from difficulties in capturing long-range dependency and understanding feature contributions. In response to these challenges, an Explainable AI framework to predict dew point using Attention-Based Temporal Convolutional Network (TCN) is proposed. The framework uses cutting-edge preprocessing methods such as cyclical temporal encoding, seasonal feature generation, normalization, and missing value handling to enhance data quality and representation. Explainable Artificial Intelligence using the SHAP method is used to determine which meteorological variables have the greatest influence and to gain transparency into model predictions. Moreover, a hybrid TCN-LSTM network is designed to capture the local temporal dependence and long-term sequential relationship. The attention mechanism allows the model to focus on the most relevant temporal patterns, resulting in more accurate forecasts. Experimental results show that the proposed attention-based TCN outperforms the conventional LSTM model and BiLSTM model in terms of prediction accuracy, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). By combining the strengths of the convolutional approach and the recurrent memory function, the hybrid TCN-LSTM model proves to be the most effective. The results obtained have shown that the proposed framework is suitable for climate sensitive applications, environmental monitoring systems, and intelligent weather prediction platforms because it is reliable and gives very accurate results for the dew point time. The results obtained have shown that the proposed framework is reliable and gives very accurate results for the dew point time that is suitable for climate sensitive applications, environmental monitoring systems and intelligent weather prediction platforms.***

Keywords: Dew Point Forecasting, Explainable Artificial Intelligence, Temporal Convolutional Network, Attention Mechanism, SHAP Analysis, Deep Learning, Climate Monitoring, LSTM, Weather Prediction, Hybrid Forecasting Models

1. Introduction

Climate change is identified as one of the most severe environmental issues impacting ecosystems, public health, agriculture and economic development globally [1]. Global warming has resulted in changes in precipitation and increased in intensity of extreme weather events [2]. The importance of accurate weather forecasting for climate adaptation and disaster preparedness has thus grown more and more urgent [3]. The role of the parameters of the atmosphere like temperature, humidity, pressure and dew point in the understanding of weather is very crucial [4]. The dew point temperature is the temperature at which the air will become saturated with water vapor [5]. It is used as a basic measure of the moisture condition of the atmosphere [6]. Dew point variations are very important in the formation of rain and development of clouds [7]. In agriculture dew point data is utilized for irrigation scheduling and crop management widely [8]. Dew point measurements are used by environmental scientists to study climate variability [9]. Dew point temperatures are measured by public health agencies for the purpose of evaluating heat stress and humidity related hazards [10]. With this in mind, the ability to forecast the dew point accurately becomes a key requirement for decision making in sectors depending on climate [11]. The traditional forecasting methods are mostly based on statistical methods including autoregressive technique and exponential smoothing [12]. Many of these methods make the assumption of linearity between variables [13]. Meteorological data, however, are very nonlinear and dynamic [14]. Thus, traditional approaches often yield less than ideal predictions [15].

Data-driven learning approaches were the new driving force in recent years, which has revolutionized meteorological forecasts thanks to the development of artificial intelligence [16]. Random Forest, Support Vector Machine and Gradient Boosting have been found to have better predictive power using machine learning algorithms [17]. Additional advantages for forecasting are provided by deep learning models that can learn complex temporal relationships from large data sets [18]. Weather prediction applications have enjoyed popularity with LSTM networks [19]. Bidirectional LSTM architectures are used to better learn sequences by integrating forward and backward context information [20]. Another interesting application is the use of CNNs combined with recurrent models for better feature extraction [21]. However, many deep learning models are yet to be effective in capturing long-range dependency [22]. Recently, Temporal Convolutional Networks have been explored which are capable of capturing the sequential information through using causal and dilated convolutions [23]. The attention mechanisms are also used to focus on the temporal features that are relevant for prediction [24]. Efforts are being made to increase transparency of models by adding Explainable Artificial Intelligence (XAI) techniques [25]. SHAP based analysis can be used to quantify the importance of features and interpret the results of the prediction [26]. Combining explainability with sophisticated forecasting systems can improve user confidence and reliability of the forecasts [27]. The proposed Attention-Based Temporal Convolutional Network takes advantage of these features to enable accurate dew point prediction [28]. To enhance the representation learning in the temporal domain, a hybrid TCN-LSTM is further developed [29]. This combined method offers interpretable, accurate and scalable forecasting for environmental monitoring applications [30].

2. Literature Survey

A few studies have been conducted on AI and deep learning methods for weather and dew point prediction. Machine learning approaches toward meteorological prediction problems have been recently discovered [1]. Forecasting systems based on Artificial Intelligence have been shown to outperform traditional statistical based forecasting systems [2]. In particular, deep learning architectures are capable of learning weather patterns of non-linear nature [3]. It has been reported that Long Short-Term Memory networks are able to predict temperature successfully [4]. Bidirectional LSTM models have been found to be better at capturing the sequential dependencies [5]. The dew point temperature and humidity have been predicted with a high level of accuracy by using Artificial Neural Networks [6]. The use of ANN-based forecasting models has been found to be beneficial in various agricultural and environmental applications [7]. Random Forest techniques were also used to forecast climate variables [8] . In weather classification tasks, Support Vector Machines are shown to be successful in getting good results [9]. The hybrid deep learning frameworks that combine CNN with recurrent model have demonstrated better forecasting performance [10]. Convolutional Neural Networks have been used to learn spatial features in meteorological data [11]. The use of Gated Recurrent Units to efficiently model temporal relationship [12] has been explored. Multi-head attention has also helped to improve feature selection and temporal pattern recognition [13]. To enhance the generalization power, ensemble learning methods have been investigated [14]. CNN-LSTM ensembles have been found to exhibit good performance for temperature forecasting in Bangladesh [15].

In recent years, more and more research has been conducted on advanced temporal learning architectures for weather prediction [16]. Temporal Convolutional Networks have proven to be a viable alternative to recurrent neural networks [17]. TCNs are able to efficiently model long-range dependencies with dilated causal convolutions [18]. In the case of complex time-series datasets, attention-based TCN models have shown to be more accurate in forecasting tasks [19]. Hybrid CNN-GRU-Attention models have been found to better perform for temperature prediction tasks [20]. It has been demonstrated that explainable AI approaches can enhance the transparency and trustworthiness of predictive systems [21]. Among the commonly used methods for feature importance evaluation, the one named SHAP stands out as one of the most widely used [22]. Explainable forecasting frameworks give insights on the contribution of meteorological variables [23]. The use of feature selection methods has considerably reduced the complexity of the models and prediction errors [24]. Hybrid forecasting systems with Recurrent and Convolutional units have shown better performance than conventional ones [25]. Deep learning methods have shown good performance in predicting the seasonal and cyclical climate [26]. Some advanced architectures have been able to get lower RMSE and MAE with various forecasting horizons [27]. Climate monitoring applications have also further benefited from the use of real time forecasting systems [28]. An emerging field of research is the combination of attention mechanisms and explainability techniques [29]. All of this paves the way for the use of explainable attention-based TCN architectures for reliable dew point prediction [30].

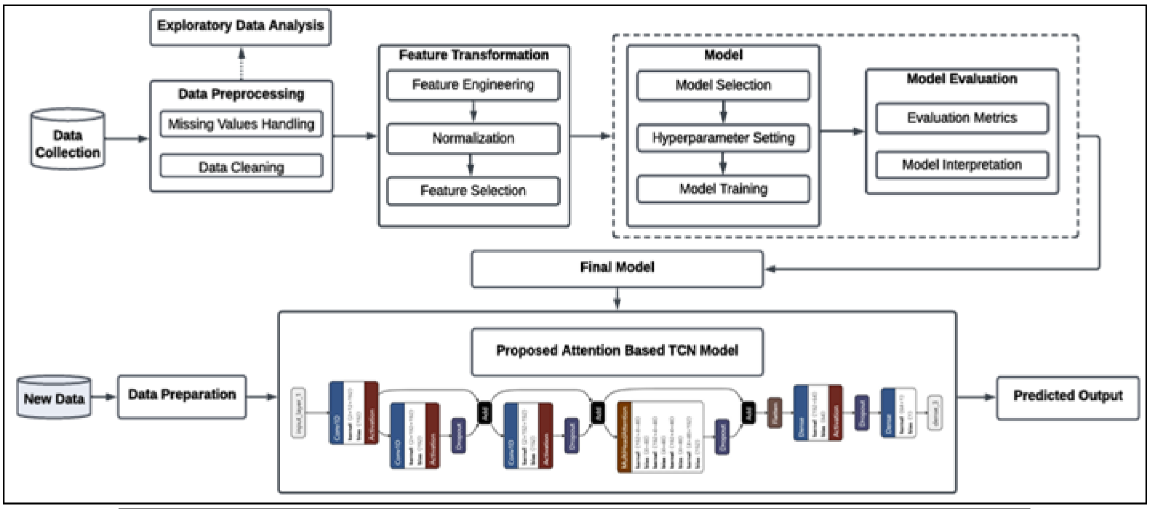
3. Proposed System

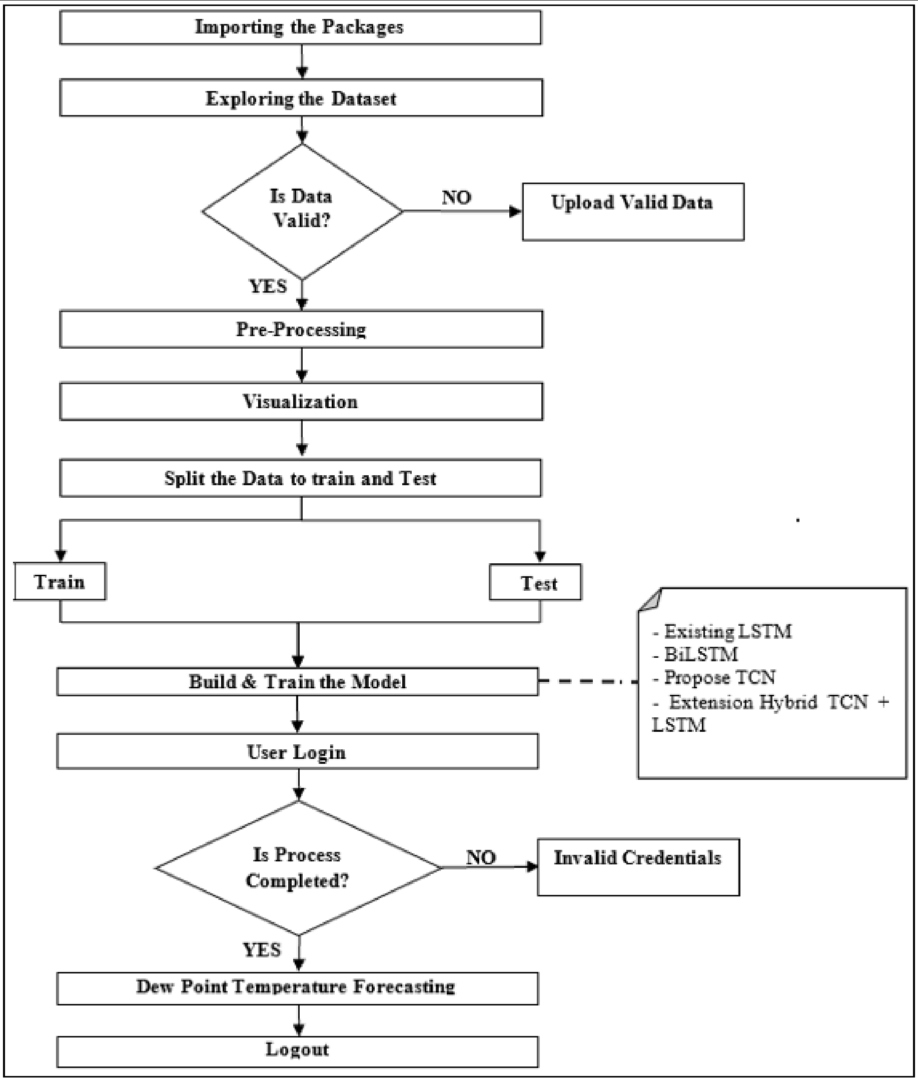
The proposed system proposes an Explainable AI-based dew point forecasting system using an Attention-based Temporal Convolutional Network (TCN) with Long Short-Term Memory (LSTM) architecture. The aim is to improve accuracy of forecasts while retaining the interpretability and transparency of the model predictions. A set of historical meteorological information: temperature, relative humidity, atmospheric pressure, wind speed, visibility, and temporal data is gathered and preprocessed at first. This is done by using suitable methods of imputation of missing values and noise reduction techniques to enhance the quality of the data. Cyclical representations using sine and cosine encoding for temporal attributes like hour, day, month, season are used to ensure periodic characteristics. Additionally, there are day-night indicators and seasonal labels created to give context. The features obtained after pre processing are normalized to provide stable and efficient training of the model. SHAP-based Explainable AI (XAI) methods are used to determine the most influential factors determining dew point prediction. Feature importance analysis allows to select a set of the most important predictors and also to reduce the number of redundant predictors and computation complexity.

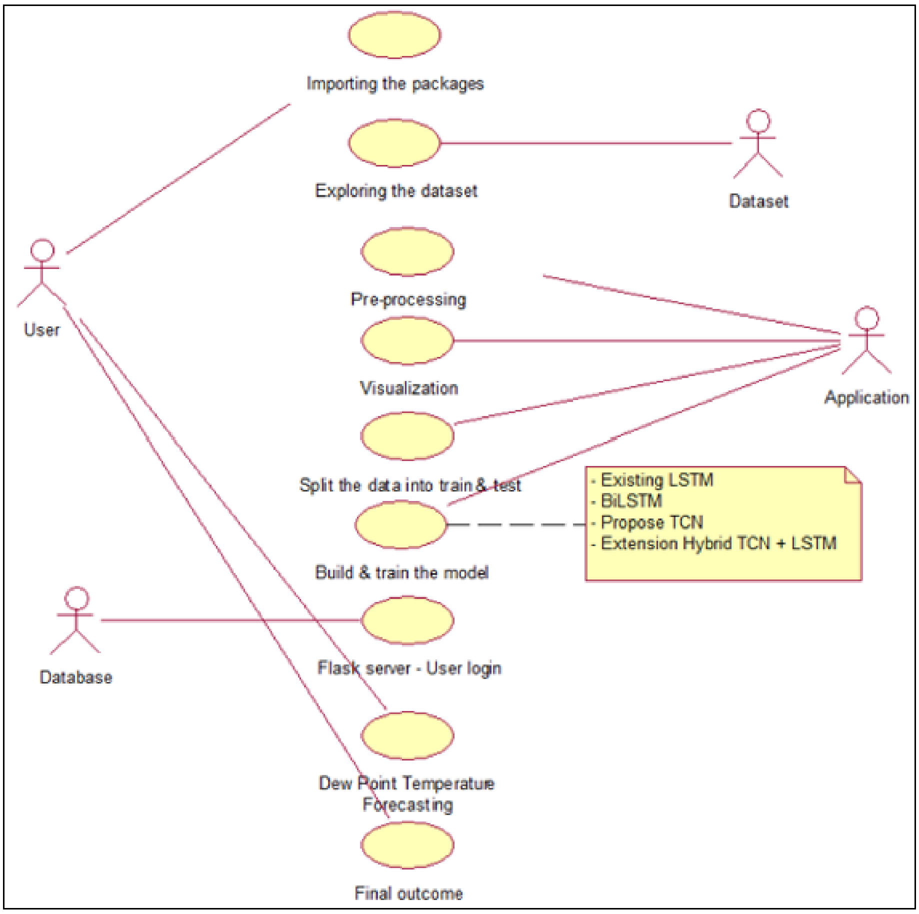
These selected features are then passed on to the proposed hybrid forecasting system. The Temporal Convolutional Network is based on dilated causal convolutions (DCC) that are able to model long-range temporal dependencies without compromising gradient degradation issues. A special attention mechanism is introduced to highlight the important temporal patterns and enhance feature representation. The LSTM module, in turn, captures the dynamics over time and the changing environmental conditions. The LSTM network's output is combined with the attention-based TCN for context-aware predictions. This hybrid scheme can make use of the convolutional feature extraction and the recurrent memory learning to enhance the forecasting accuracy. MAE, RMSE, and R^2 are used to evaluate the forecasting results obtained. A web application has been also developed using Flask to create a user friendly interface to upload meteorological data and get real-time dew point prediction. The system is expected to provide better forecasting accuracy, improved interpretability, and implementability in the fields of climate monitoring, environmental analysis, climate planning for agriculture, and weather-based decision support systems.

4. System Design

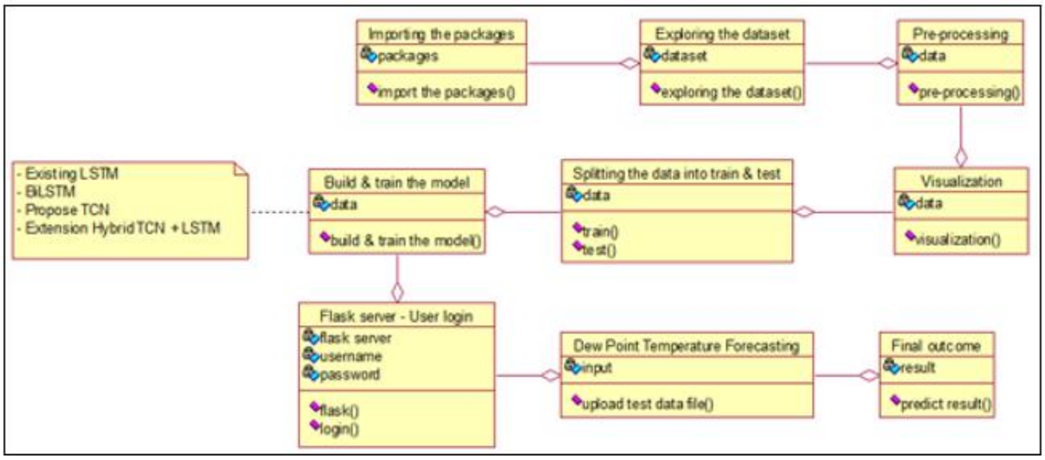
The system design is a multi-modular system that should be interconnected in order to derive dew point forecast. The architecture starts with a data acquisition module for the collection of historical meteorological data from weather stations and climate databases. The data gathered are sent to the preprocessing module where missing values, outliers, and inconsistencies are dealt with systematically. Temporal feature engineering involves creating cyclic representations of hours, days and seasonal indicators. The input variables are then normalized using data normalization techniques to enable deep learning models to process the variables on a common scale. The feature selection module uses Explainable Artificial Intelligence (SHAP) after preprocessing to measure the importance of the features to the prediction results. Significant meteorological parameters like temperature, humidity, wind speed, pressure and meteorological attributes of the season are identified and retained for model development. The data obtained is then split into a training set and a testing set for the construction and validation of the model.







The forecasting engine is the key element of the system architecture. These include the existing LSTM model, the proposed Attention-Based Temporal Convolutional Network, and the proposed enhanced model of Hybrid TCN-LSTM. To deal with long-range temporal dependencies efficiently, the TCN component is composed of causal and dilated convolutional layers. The attention mechanism highlights the temporal parts that are important and weights the important observations with larger weights. The LSTM network is used with the TCN to learn sequential changes and temporal transitions in the dataset. The forecasting performance of the forecasting engine is assessed by statistical metrics such as RMSE, MAE and R^2. A visualization module provides feature importance rankings, forecast trends and model comparisons in graphical format. Lastly, the deployment module includes a web interface using the flask framework, enabling users to upload test datasets, execute the forecasting tasks, and retrieve the forecasting results live. The modular design makes it easy to scale up, interpret, ensure reliability, and integrate in the future to fit environmental monitoring projects.



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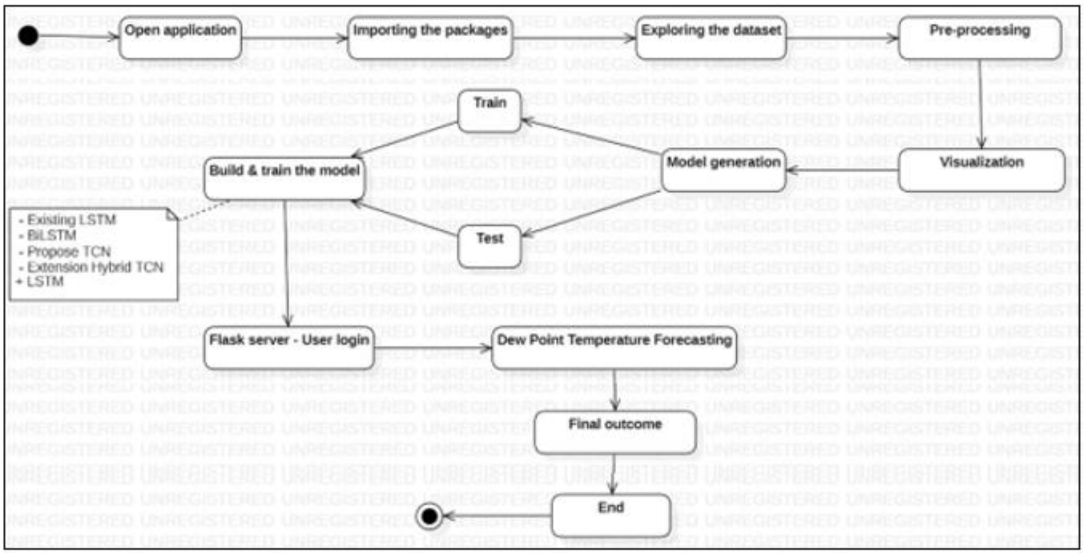

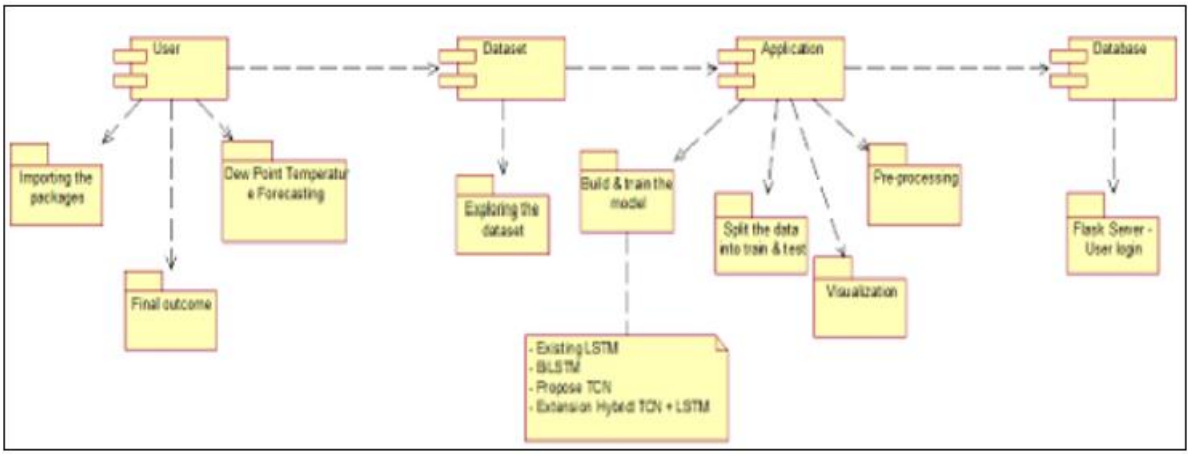

5. Results & Discussion

The forecasting ability of the proposed forecasting framework is tested with hourly meteorological data sets and benchmarked against other deep learning models, such as LSTM and BiLSTM. Experimental results show that the proposed Attention-Based Temporal Convolutional Network has a significant ability to capture the nonlinear relationship and long-range temporal dependency, which has improved the accuracy of dew point prediction. The classical LSTM model showed good forecasting accuracy but it did not perform well in case of complex seasonal patterns and long time series. Incorporating bidirectional learning, BiLSTM enhanced the ability of prediction, yet the errors of prediction remained relatively higher in rapidly changing environments. The proposed Attention-Based TCN exhibited R^2 values of around 0.798 along with lower mean absolute error and root mean square error values, which demonstrated the better forecasting performance. The introduction of attention mechanisms allowed the model to focus on and highlight important temporal patterns, enhancing the consistency of predictions and minimizing forecasting uncertainty. SHAP analysis also identified the influence of the most important variables, such as temperature, relative humidity, seasonality indicators, and wind speed, on the accuracy of dew point prediction.

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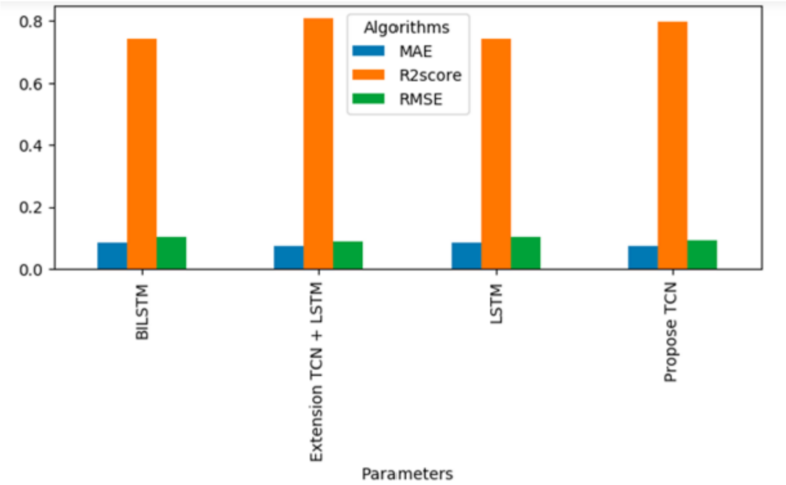
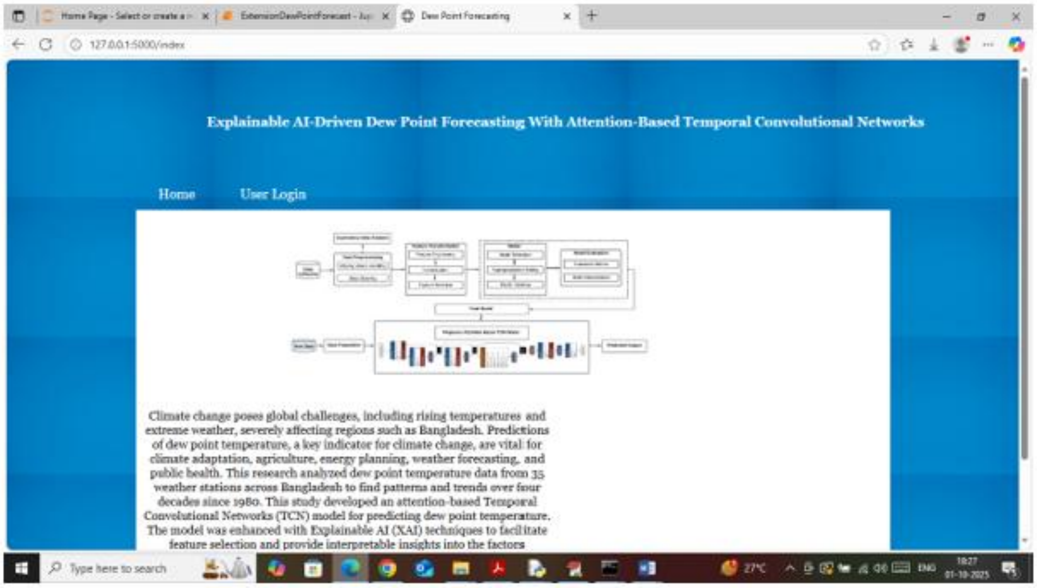
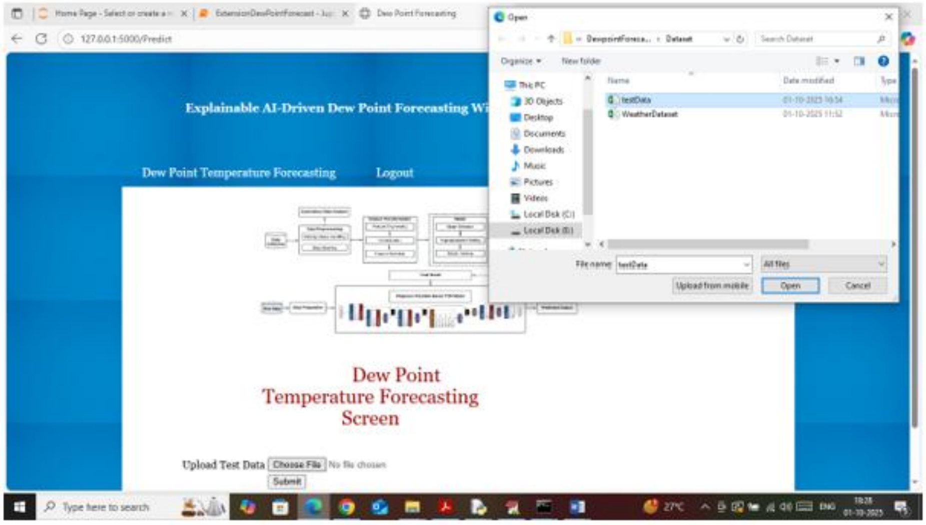
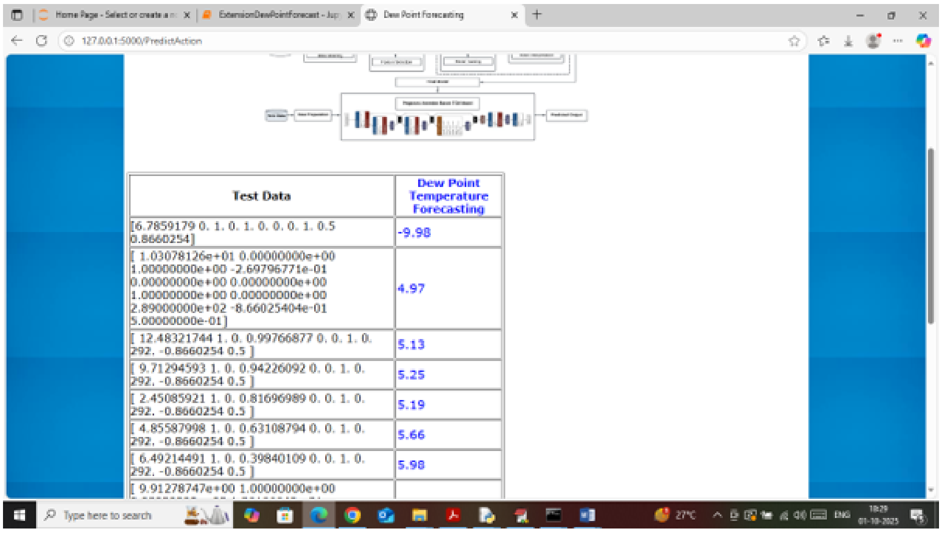


Comparison Graph







A hybrid TCN-LSTM model, building on the advantages of convolutional and recurrent learning models, was designed to further boost the performance. The experimental results showed that the hybrid model performed better than all other baseline models with the highest R^2, ~0.886, and the lowest MAE and RMSE values out of the evaluated models. The hybrid architecture was found to be useful for capturing both local temporal structures and the long-term sequential dependence, leading to more powerful forecasting performance. Actual and predicted values were compared visually and good agreement was seen between actual and predicted dew point temperatures. Feature importance analysis gave insight into the decision making process of the model and made users more confident in the modelling process. The findings show that the hybrid deep learning architectures, accompanied with attention mechanisms and explainable AI techniques, substantially improve forecasting accuracy. Therefore, the proposed framework can be considered to be a practical, and understandable, solution to the problem of climate monitoring, environmental management, agricultural planning, and disaster preparedness applications that require an accurate prediction of dew point.

6. Conclusion

In this study, an Explainable AI based framework for predicting dew point temperature was developed with the help of Attention-Based Temporal Convolutional Network (ATCN) architecture along with Long Short-Term Memory (LSTM). Correct dew point prediction is of great importance in climate monitoring and management, environmental management, agricultural planning and disaster prevention. Common statistical and machine learning methods do not adequately represent the long-term dependency, seasonality and non-linearity found in meteorological data. To address these shortcomings, this framework used a combination of sophisticated techniques such as advanced preprocessing, cyclical temporal encoding, and seasonal feature engineering, along with SHAP-based feature importance analysis and attention-enhanced temporal convolutional learning. The proposed model, namely Attention-Based TCN, was experimentally evaluated and it was found to be more effective than the conventional LSTM model and BiLSTM model in terms of forecasting accuracy. Moreover, the hybrid TCN-LSTM model outperformed all other models by successfully capturing the features using convolution and retaining the features using LSTM. Using XAI with the SHAP algorithm to increase model transparency, influential meteorological variables were identified and the nature of prediction outcomes was explained.The use of Explainable Artificial Intelligence (XAI) and the SHAP algorithm increased the transparency of the model by identifying influential meteorological variables and generating interpretable explanations of prediction outcomes. The results showed significant decreases in prediction errors and increases in coefficient of determination values. The proposed framework is thus a reliable, scalable and interpretable approach for hourly dew point forecasting. Furthermore, it is implemented in a practical way using a Flask-based web interface, which further enhances the utility of this for real-time environmental monitoring and decision-making applications. In future work, transformers for forecasting architectures, multi-location climate datasets, adaptive attention mechanisms, and federated learning frameworks can be explored to enhance the robustness and scalability of climate predictions. The overall developed forecasting system is a great step forward in the direction of intelligent climate analytics, and the explainable weather prediction system.

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