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AIWFF: A Machine Learning based Framework for Automatic Weather Forecasting

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Abstract: In the contemporary era witnessing global warming effects, weather is a dynamic phenomenon which is highly uncertain. The conventional approaches that rely on certain physical processes governing atmosphere are capable of serving a great deal in weather forecasting. However, robustness to perturbations is still desired. In this content Artificial Intelligence (AI) innovations assume significance to bring about more reliable forecasting alternative which may complement conventional methods. In this paper, we proposed a framework known as AI-enabled Weather Forecasting Framework (AIWFF) which exploits machine learning (ML) models that are robust to time series data and underlying perturbations for improving forecasting performance. An algorithm known as Learning based Intelligent Weather Forecasting (LIWF) is proposed and implemented. This algorithm has required pre-processing, feature section and a pipeline of ML models to learn from data and then forecast weather more accurately. Another algorithm known as Hybrid Method for Feature Selection (HMFS) is proposed to leverage training quality in LIWF algorithm. The framework results in three trained knowledge models saved to secondary storage. These models are known as Random Forest Regressor, Linear Regressor and Decision Tree Regressor. An application with Graphical User Interface (GUI) is developed to make use of these knowledge models and provide forecasting on user requests. The empirical results revealed that the proposed framework shows better performance.

Keywords: Weather Forecasting, Artificial Intelligence, Machine Learning, Regression Models, Learning Based Weather Forecasting.

I. INTRODUCTION

Weather forecasting is found very important for many decades. Of late, due to emergence of Internet of Things (IoT) and AI, it became more significant due to unprecedented possibilities. Many applications linked to agriculture, generation of renewable energy and aviation, to mention few, rely on weather forecasting. When compared to traditional approaches that relied on physical observations, ML models brought more robustness and accuracy in prediction of weather conditions [1]. With the applications based on weather forecasting are increasing the research associated with weather has assumed more significance. In this regard, learning based approaches that learn from historical data became important as they exploit existing patterns and perform more accurate predictions. Agriculture is one of the domains where weather forecasting plays an important role in sowing seeds, making crop related decisions and harvesting dynamics. In the wake of emerging technologies used for precision agriculture, ML models became crucial for improving prediction performance.

There are many existing methods based on ML and deep learning techniques. Naveen and Mohan [4] explored different existing approaches on multi-scale forecasting, ML models and optimization models for weather forecasting. They found that Neural Network (NN) based models could improve prediction performance. Sogabe *et al*. [5] proposed a methodology to exploit ML models to forecast weather and plan a renewable energy system with optimal production. Haupt *et al*. [7] studied ML models for prediction of weather details. Haupt and Kosovic [8] combined the concept of big data and various ML methods to arrive at a system for applied weather forecasting. Aznarte and Siebert [12] considered the problem of dynamic line rating (DLR) associated with weather prediction using ML techniques. Their system has analysis of risk factors and provide appropriate risk alarms as well. Ren *et al*. [6] explored different deep learning approaches for forecasting weather. Those models are categorized into Deep Neural Network (DNN) models, hybrid models and combination of NWP and DNN models. Peng *et al*. [16] proposed a prediction model known as EALSTM-QR for wind power prediction. It is based on a deep learning mode known as LSTM and also Quantile Regression (QR). With historical wind power data and feature extraction, their method could perform better than state of the art. Conventional approaches that rely on certain physical processes governing atmosphere are capable of serving a great deal in weather forecasting. However, robustness to perturbations is still desired. Towards this end ML models came into existence. However, there is need for leveraging prediction performance with appropriate feature selection integrated with the prediction framework. Our contributions in this paper are as follows.

1. We proposed a framework known as AI-enabled Weather Forecasting Framework (AIWFF) which exploits machine learning (ML) models.
2. An algorithm known as Learning based Intelligent Weather Forecasting (LIWF) is proposed and implemented. This algorithm has required pre-processing, feature section and a pipeline of ML models to learn from data and then forecast weather more accurately.
3. We proposed another algorithm known as Hybrid Method for Feature Selection (HMFS) to improve training quality of ML models.
4. An application with Graphical User Interface (GUI) is developed to make use of the saved knowledge models and provide forecasting on user requests.

The remainder of the paper is organized as follows. Section 2 reviews related works on ML based weather forecasting. Section 3 presents the proposed framework known as AI-enabled Weather Forecasting Framework (AIWFF). Section 4 presents experimental results while Section 5 concludes our work and talks about future scope of the research.

II. RELATED WORK

This section reviews related works focused on ML techniques for weather forecasting. Singh *et al*. [1] proposed a weather forecasting model based on Random Forest (RF) model. It was a supervised learning method with GUI for prediction of weather. Sharma *et al*. [2] focused on prediction of solar power generation dynamics based on an integrated weather forecasting module. Based on prediction of weather, multiple regression models are employed to know the solar power generation dynamics. In future then intend to incorporate their method to smart home use cases. Hewage *et al*. [3] proposed a hybrid weather forecasting model based on two techniques known as Temporal Convolutional Networks (TCN) and Long Short Term Memory (LSTM). Two regression models namely multi-input single output (MISO) and multi-input multi-output (MIMO) are used to evaluate their hybrid model. In future, they intend to improve their method to support a short term weather forecasting system. Naveen and Mohan [4] explored different existing approaches on multi-scale forecasting, ML models and optimization models for weather forecasting. They found that Neural Network (NN) based models could improve prediction performance. Sogabe *et al*. [5] proposed a methodology to exploit ML models to forecast weather and plan a renewable energy system with optimal production.

Ren *et al*. [6] explored different deep learning approaches for forecasting weather. Those models are categorized into Deep Neural Network (DNN) models, hybrid models and combination of NWP and DNN models. Haupt *et al*. [7] studied ML models for prediction of weather details. Haupt and Kosovic [8] combined the concept of big data and various ML methods to arrive at a system for applied weather forecasting. They intend to improve it towards optimal generation of renewable energy. Purwandari *et al*. [9] proposed a methodology based on Twitter data in order to model a system using ML techniques for weather forecasting. It employs text mining and ML models like Support Vector Machine (SVM) towards realizing a multi-class weather forecasting system. Moosavi *et al*. [10] focused on studying many weather forecasting models and quantify uncertainty involved in weather forecasting models. They intend to improve it further by considering diurnal effects besides using advanced deep learning models like LSTM.

Rasouli *et al*. [11] proposed a system which considers climate and weather inputs and exploit ML models for streamflow forecasting. They found that non-linear models could perform better than linear counterparts. They intend to improve it further using seasonal conditions and extreme events for improving forecasting performance. Aznarte and Siebert [12] considered the problem of dynamic line rating (DLR) associated with weather prediction using ML techniques. Their system has analysis of risk factors and provide appropriate risk alarms as well. Rodrigues *et al*. [13] considered low resolution predictions and with high-resolution representation towards more efficient weather forecasting. It makes use of deep learning technique for learning from historical data. Saloux and Candanedo [14] focused on estimation of short-term thermal energy demand in a given district using ML models. Their method is found to be lacking with autoregressive models and they intend to improve it to enhance it further. Dolara *et al*. [15] investigated on weather estimation based approach for wind power forecasting. They employed neural networks towards wind power predictions. Their method is a hybrid model that could improve prediction performance.

Peng *et al*. [16] proposed a prediction model known as EALSTM-QR for wind power prediction. It is based on a deep learning mode known as LSTM and also Quantile Regression (QR). With historical wind power data and feature extraction, their method could perform better than state of the art. Karvelis *et al*. [17] proposed a methodology where a microcontroller is designed with embedded ML models for weather prediction. Towards this end they proposed an

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algorithm based on a regression model. They used real data collected from a ship for experiments. Chen *et al*. [18] proposed a method for decision making in the growing of rice crop. However, the decision making is based on the weather forecasts. The reinforcement learning is associated with Deep Q-learning Network (DQN) approach. It could forecast part irrigation dynamics along with forecasting rainfall patterns. Kunjumon *et al*. [19] explored different ML models including Artificial Neural Network (ANN) for forecasting weather conditions. Jain and Ramesh [20] proposed a method for weather forecasting and use the same to select crops that are conducive to the weather conditions. Their system not only suggests suitable crop but also sowing time. In future, then intend to improve it with an IoT use case for capturing weather data. Other research contributions found in literature are [21]-[30] with different ML models. Conventional approaches that rely on certain physical processes governing atmosphere are capable of serving a great deal in weather forecasting. However, robustness to perturbations is still desired. Towards this end ML models came into existence. However, there is need for leveraging prediction performance with appropriate feature selection integrated with the prediction framework.

III. PROPOSED METHODOLOGY

This section presents the proposed AI enabled framework, dataset details, feature selection method and the proposed algorithms besides evaluation procedure.

3.1 The Framework

We proposed a framework known as AI-enabled Weather Forecasting Framework (AIWFF) for efficient forecasting of weather details. The framework is presented in Figure 1. It is realized by using a hybrid approach consisting of feature selection and machine learning models. It is a data science approach that exploits regression models for making knowledge models by learning from training data. Each model is a learned model that comprehends historical data. It is supervised learning approach that learns from training data and

performs forecasting based on the knowledge gained. Since sufficient training samples are available, this kind of learning is preferred in this paper. When compared with traditional weather prediction models that are based on the current physical properties, ML models have advantage of learning from historical data. Thus unprecedented possibilities are in place with AI enabled approaches for forecasting. Once a forecasting model is evaluated and its acceptable accuracy level is witnessed, such model can be exploited by defining a web service which can be invoked in inter-operable fashion.

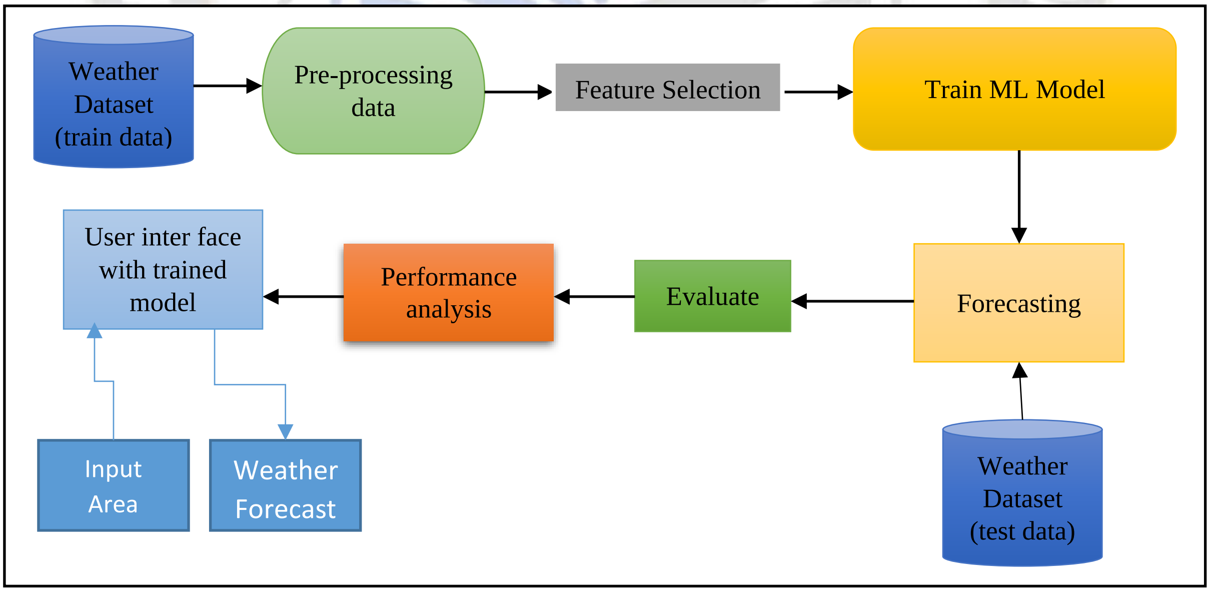

Figure 1: AI-enabled Weather Forecasting Framework (AIWFF)

As presented in Figure 1, the proposed framework is AI enabled. It exploits different ML models. It is supervised learning approach in which the given training data is subjected to pre-processing and feature selection. Our feature selection algorithm is presented later in this section. It is designed to improve training quality. After feature selection process, the features contributing to the forecasting are used to train ML models. The trained models are saved to persistence storage. Then they are used to work on the test data for forecasting. The proposed framework also supports a

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GUI application that takes user inputs and performance forecasting. Different ML models such as Linear Regression, DT Regression and RF Regression are used for forecasting. Logistic Regression is a statistical model which models a binary dependent variable by using a logistic function. It is also known as sigmoid function which is as given in Eq. 1.

$$F(x)=\frac{1}{1+e^{-x}}=\frac{e^{x}}{e^{x}+1} \qquad (1)$$

This function helps the model to obtain values required by binary classification. If p(x), an unbounded linear function, is assumed as linear function, probability is denoted by p which ranges from 0 to 1. To solve the problem, let log p(x) is a linear function and log p(x)/(1-p(x)) is expressed as in Eq. 2.

$$\mathrm{Log}\frac{p(x)}{1-p(x)} = \alpha_0 + \alpha . x \qquad (2)$$

Once the problem of p(x) is solved, it can be expressed as in Eq. 3.

$$P(x)=\frac{e^{\alpha_0+\alpha}}{e^{\alpha_0+\alpha}+1} \qquad (3)$$

In order to make logistic regression as a linear function there is need for a threshold which is set to 0.5 and rate of misclassification is minimized.

Decision Tree is another algorithm used in the proposed framework. It models given data in the form of a tree so as to converge into useful decisions. In order words, it solves given problem with tree representation of data. It makes use of two important measures known as entropy and Gini index. Entropy is computed as in Eq. 4.

$$\mathrm{Entropy}=-\sum_{i=1}^{n} p_i * \log(p_i) \qquad (4)$$

Gini index is another measuring for knowing inequality. It results in a value between 0 and 1. Lowest value indicates homogenous elements while higher value indicates heterogeneous elements indicating maximum inequality. This measure reflects sum of the square of probabilities associated with each class. It is computed as in Eq. 5.

$$\mathrm{Giniindex}=1-\sum_{i=1}^{n} {p_i}^2 \qquad (5)$$

Random Forest is another popular ML technique. It makes use of many decision trees internally. It gets predictions of all trees and make a final decision.

3.2 Dataset Description

Weather data is collected from [31]. It is the data of the year 2020. It has different attributes that are provided in the form of CSV files.

3.3 Feature Selection

Feature engineering is phenomenon widely used for dimensionality reduction in given dataset. It is importance because it has ability to compute featue importance and remove unimportant features. Based on the data distribution in the traininig data, feature importance is computed and highly contributing features are selected.

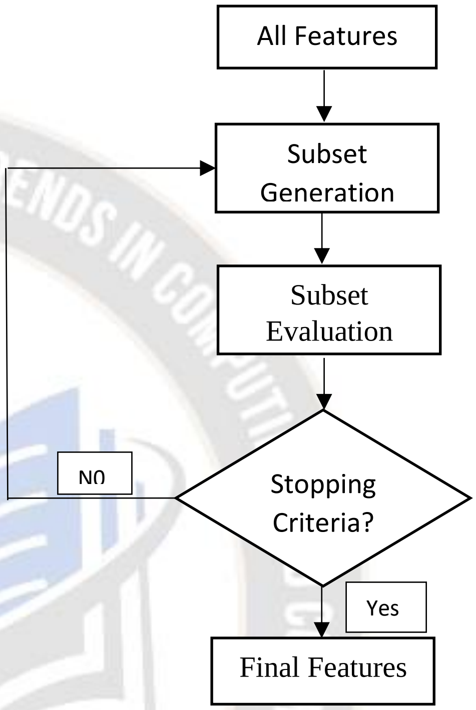

Figure 2: General feature selection procedure

As presented in Figure 2, the general approach is a filter based approach that is meant for reducing features. It has an iterative procedure to constantly verify the utility of features and finally choose features that satisfy given criteria.

Table 1: Notations involved in hybrid feature selection method

Notation	Description
$\mu_1(i)$ and $\sigma_i(i)$	Mean value
n_1 and n_0	Null class and unitary class patterns respectively
KL-distance	A distance measure
P	Represents probability distribution
Q	Represents the target probability distribution

[1]Table 1 presents different notations used in the feature engineering method which is based on three metrics namely fisher score, T-test and Kullback-Leibler divergence. Eq. 6 shows computation of fisher score.

$$F(i) = \left|\frac{\mu_1(i)-\mu_0(i)}{\sigma_1^2(i)-\sigma_0^2(i)}\right| \qquad (6)$$

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Fisher score reflects the significance of each feature while T-test is another metric used for finding feature importance. T-test is computed as in Eq. 7.

$$t(i) = \left| \frac{\mu_1(i) - \mu_0(i)}{\sqrt{\frac{\sigma_1^2(i)}{n_1} + \frac{\sigma_0^2(i)}{n_0}}} \right| \qquad (7)$$

The third measure used in the feature selection method is known as Kullback-Leibler divergence. It is computed as in Eq. 8.

$$\mathrm{KL}(p, q) = \sum_i p_i \log_2\left(\frac{p_i}{q_i}\right) \qquad (8)$$

By combining these three measures a composite metric is generated and used for identification of useful features.

3.4 Proposed Algorithms

We proposed two algorithms for efficient weather forecasting. Hybrid Method for Feature Selection (HMFS) is proposed towards feature engineering while Learning based Intelligent Weather Forecasting (LIWF) is proposed for intelligent forecasting.

Algorithm: Hybrid Method for Feature Selection (HMFS)
Input:
Dataset *D*
threshold *th*
Output: Chosen features F

1. Begin
2. *A*←GetAttributes(*D*)
3. For each *a* in *A*
4. *f*←ObtainFeatures(*a*)
5. *F*←*F*+*f*
6. End For
7. For each *f* in *F*
8. fs←ComputeFS(f,F) using $F(x) = \frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1}$
9. *ts*←ComputeTS(*f*, *F*) using $t(i) = \left| \frac{\mu_1(i) - \mu_0(i)}{\sqrt{\frac{\sigma_1^2(i)}{n_1} + \frac{\sigma_0^2(i)}{n_0}}} \right|$
10. *res*←ComputeRES(*f*, *F*) using KL(p, q) $= \sum_i p_i \log_2\left(\frac{p_i}{q_i}\right)$
11. *ms*←FindMS(*fs*, *ts*, *res*)
12. IF ms >=th Then
13. Add *f* to F'
14. End For
15. Return *F'*
16. End

Algorithm 1: Hybrid Method for Feature Selection (HMFS)

[1]Algorithm 1 is used to compute feature importance for every feature in the dataset. It filters features from given dataset D and chooses certain features that have capacity to improve forecasting performance. It makes use of three filter methods combined to have a hybrid approach for feature selection. Another algorithm known as Learning based Intelligent Weather Forecasting (LIWF) is proposed for efficient weather forecasting.

Algorithm: Learning based Intelligent Weather Forecasting (LIWF)

Inputs: Dataset D, ML techniques M
Output: Forecasting Results R

1. Begin
2. (*T1*, *T2*)←SplitDataset(*D*)
3. *F*←HMFS(*T1*)
4. For each machine learning model m in M
5. m←Perform model training using F
6. FitTheModel(m, T2)
7. R←PerforForecast(m, T2)
8. Save model m
9. Compute Accuracy
10. Compute MSE
11. Display R
12. Display Accuracy
13. Display MSE
14. End For
15. For each saved model m in M
16. Take newly arrived data
17. Forecast weather using saved model m
18. End For
19. End

Algorithm 2: Learning based Intelligent Weather Forecasting (LIWF)

[2]Algorithm 2 uses given dataset and ML model pipeline and for weather forecasting. The data is split into training and testing. HMFS algorithm is reused to find best features. Afterwards every model from pipeline is used to perform training process. After completion of learning from data, each model is given opportunity to perform forecasting. Then the performance of each model is evaluated. Each trained model is saved and thus they can be reused with the GUI application to forecast weather on demand.

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3.5 Performance Evaluation Metrics

Performance of the proposed ML algorithm is determined based on its ability to correctly forecast. Based on the forecast and ground truth accuracy of the models is computed. Mean Absolute Error (MAE) is another metric used to evaluate the performance of models.

Table 2: Performance metrics used for evaluation

Metric	Formula	Value range	Best Value
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	[0; 1]	1
MAE	$mae = \frac{\sum_{i=1}^{n} abs\,(y_i - \lambda(x_i))}{n}$	[0; 1]	0

[2]As presented in Table 2, accuracy and MAE are two metrics used to evaluate performance of the forecasting models. MAE computes average of absolute errors in the forecasting process. It is a kind of loss function which is commonly used. It can be used to optimize learning problems.

IV. RESULTS AND DISCUSSION

This section presents experimental results of the proposed framework with underlying forecasting models. MAE and accuracy are the two metrics used evaluate the models.

Table 3: Forecasting model accuracy comparison

Forecasting Model Name	ACCURACY
Linear Regression	96.29
DT Regression	93.37
RF Regression	96.45

[3]As presented in Table 3, the forecasting models are evaluated with observations in terms of accuracy.

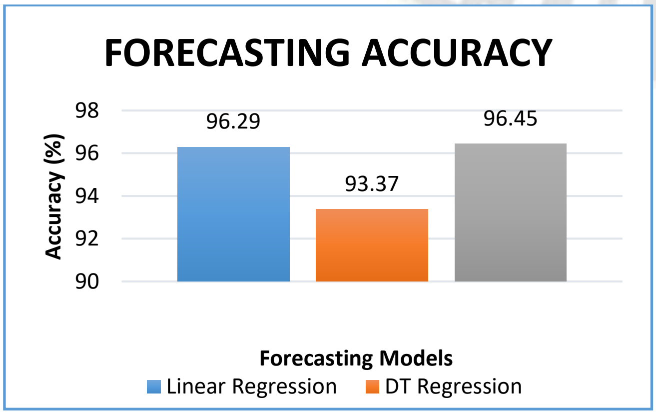

Figure 3: Forecasting performance comparison in terms of accuracy

[3]As presented in Figure 3, accuracy of different forecasting models is provided. Higher in accuracy indicates better performance. Each forecasting model showed different level of accuracy. The rationale behind this is that the models do have different modus operandi in prediction process. The accuracy of DT regression model is least with 93.37% accuracy. LR model showed 96.29% accuracy. Highest accuracy is exhibited by RF regression model with 96.45%.

Table 4: MAE comparison

Forecasting Model Name	MAE
Linear Regression	5.34
DT Regression	8.60
RF Regression	4.68

[4]As presented in Table 4, MAE observations are provided for each forecasting model used in the proposed framework.

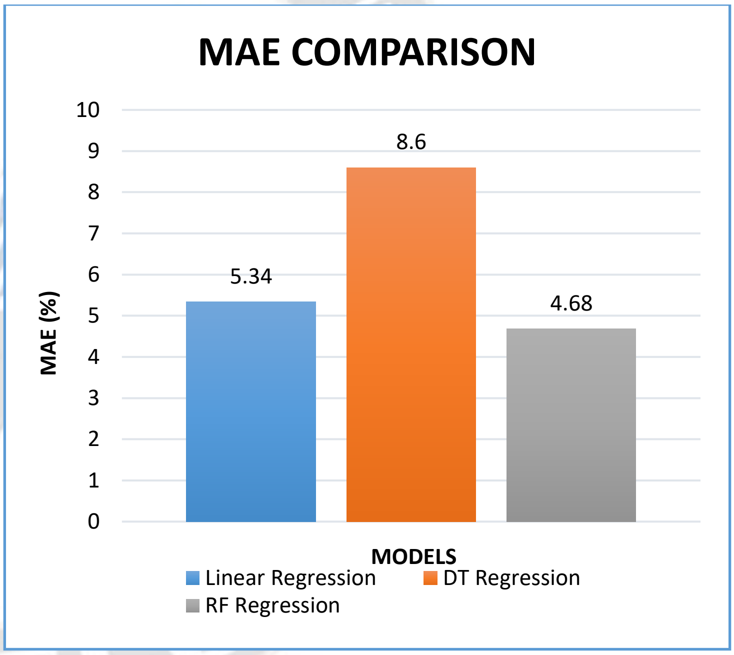

Figure 4: Forecasting performance comparison in terms of accuracy

[4]As presented in Figure 4, MAE of different forecasting models is provided. Lower in MAE indicates better performance. Each forecasting model showed different level of MAE. The rationale behind this is that the models do have different modus operandi in prediction process. The MAE of DT regression model is highest with 8.6% accuracy.

LR model showed 5.34% MAE. Least MAE is exhibited by RF regression model with 4.68%.

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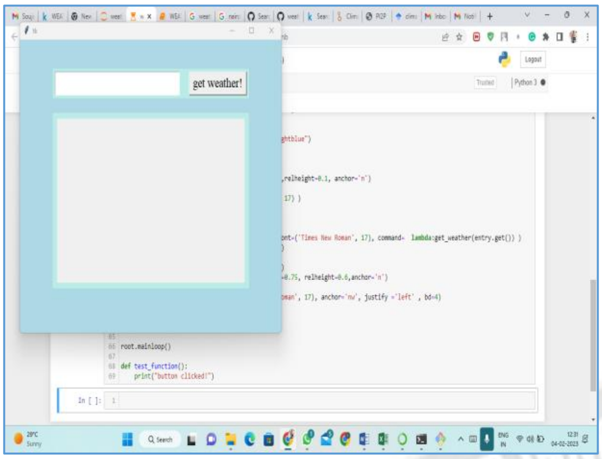

Figure 5: Visualizing user interface for weather forecasting

[5]As presented in Figure 5, the saved foresting models can be reused for forecasting of weather based on user inputs.

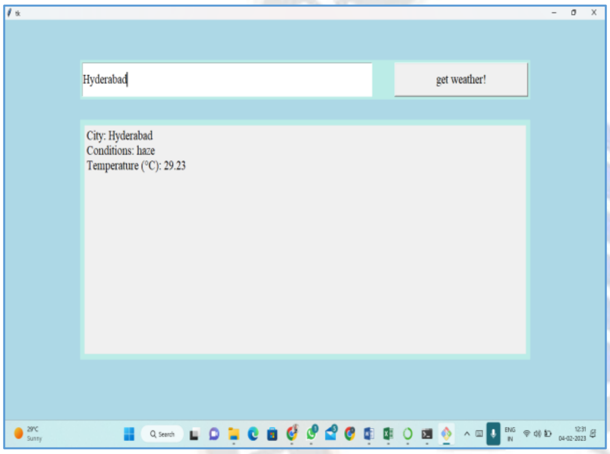

Figure 6: Visualizing user interface for weather forecasting

[6]As presented in Figure 6, the saved foresting models can be reused for forecasting of weather based on user inputs. Provided a city, it is able to provide its forecasts.

V. CONCLUSION AND FUTURE WORK

In this paper, we proposed a framework known as AI-enabled Weather Forecasting Framework (AIWFF) which exploits machine learning (ML) models that are robust to time series data and underlying perturbations for improving forecasting performance. An algorithm known as Learning based Intelligent Weather Forecasting (LIWF) is proposed and implemented. This algorithm has required pre-processing, feature section and a pipeline of ML models to learn from data and then forecast weather more accurately. Another algorithm known as Hybrid Method for Feature Selection (HMFS) is proposed to leverage training quality in LIWF algorithm. The framework results in three trained knowledge models saved to secondary storage. These models are known as Random Forest Regressor, Linear Regressor and Decision Tree Regressor. An application with Graphical User Interface (GUI) is developed to make use of these knowledge models and provide forecasting on user requests. The empirical results revealed that the proposed framework shows better performance. Highest performance is exhibited by RF regression model with 96.45% accuracy. In future, we intend to propose a hybrid prediction model that combines linear and non-linear models towards leveraging weather forecasting performance.

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