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Research article

Predicting Dew Point Temperatures: A Machine Learning Approach with SHAP Explanations

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Abstract: In industrial production, controlling the dew point temperature is crucial for maintaining operational efficiency and product quality. This research aims to apply machine learning models to predict dew point temperatures and enhance model interpretability using SHapley Additive exPlanations (SHAP) to explain feature contributions. The data was collected from an Industrial Internet of Things (IIoT) system, and models evaluated include Linear Regression, Ridge Regression, Lasso Regression, Decision Trees, Random Forest, Gradient Boosting, XGBoost, Support Vector Regression (SVR), and k-Nearest Neighbors (KNN). The results indicated that the Random Forest model performed best, with the highest R^2 (0.94) and the lowest RMSE (0.82). Other well-performing models include Gradient Boosting, with an R^2 of 0.93 and an RMSE of 0.86, and XGBoost, with an R^2 of 0.93 and an RMSE of 0.87. For model interpretability, the real-time power consumption of the system ("ACTIVE POWER"), supply air temperature ("TEMP IN"), and supply air humidity ("HUM IN") were identified as important factors influencing the predictions. The SHAP analysis provided local and global insights into feature importance, enabling more informed decision-making in dew point control. These findings demonstrate the potential of integrating machine learning and explainable AI in industrial applications to advance operational strategies and safety measures.

Keywords: SHAP; Explainable AI; Machine learning; Dew point prediction

1. Introduction

Recent Internet of Things (IoT) technology developments have significantly transformed industrial production. Industry 4.0, often called the fourth industrial revolution, emphasizes the integration of intelligent computing and networking technologies into manufacturing processes. The primary goal of this integration is to improve automation, reliability, and control, resulting in the emergence of the Industrial Internet of Things (IIoT). IIoT specifically focuses on leveraging IoT technology to create interconnected systems that facilitate communication and data exchange throughout the manufacturing landscape, ultimately enhancing productivity, efficiency, safety, and overall intelligence [1, 2]. By combining operational data with meteorological and power grid information, advanced methodologies such as big data analytics, load forecasting, and machine learning are being employed to optimize operational efficiency and energy consumption within industrial settings. These analytical techniques have found extensive application in several research areas, including

meteorology, environmental studies, and the analysis of thermodynamic variables in industrial processes [3].

Managing the dew-point temperature in industrial production is essential for ensuring both safety and product quality, as it directly affects the efficiency of energy-intensive equipment. This issue has gained increased attention in several industrial processes. According to ISO 8573-1 [4], which provides general information about contaminants in compressed air systems, the dew point is the temperature at which water vapor condenses. When the ambient temperature drops below this point, water vapor condenses, leading to fog or frost formation. Such condensation can disrupt normal operations, create safety hazards, and result in significant property damage within industrial environments. As modern production standards rise, companies emphasize maintaining optimal dew-point levels to ensure operational safety, improve production quality, and support technological advancements. In precision manufacturing, high humidity accelerates corrosion of metal parts, interferes with mold processes, and damages machinery. Therefore, controlling the dew-point temperature is critical to industrial upgrades and process improvements [3].

Researchers have applied machine learning techniques to address these challenges to estimate and predict environmental dew-point temperatures, achieving promising results [3, 5, 6]. These models demonstrate strong capabilities in identifying complex data patterns, leading to improved prediction accuracy and operational performance. However, despite their strong predictive capabilities, it isn't easy to interpret how machine learning models make predictions. This challenge emphasizes the growing importance of Explainable Artificial Intelligence (XAI), which has acquired significant interest in recent years [7-9]. XAI encompasses methods designed to make machine learning models more transparent and interpretable for human users. The primary purpose of XAI is to explain how these machine learning models function internally, enabling users to understand better, trust, and manage their outputs effectively.

One of the most interesting XAI technologies developed in recent years for interpreting machine learning models is SHAP (SHapley Additive exPlanations). SHAP has become a widely used tool for model interpretability across various fields [10-13]. SHAP assigns a value to each feature's contribution to a model's predictions, offering a consistent feature importance measure. By quantifying the influence of individual features, SHAP helps clarify how they impact a model's outcomes. This interpretive approach not only boosts transparency but also aids in validating and comprehending complex machine learning models' decision-making processes.

This research aims to employ machine learning techniques to predict dew point temperatures using data collected from an Industrial Internet of Things (IIoT) system. The analysis integrates various methods, including Linear Regression, Ridge Regression, Lasso Regression, Decision Trees, Random Forest, Gradient Boosting, XGBoost, Support Vector Regression (SVR), and k-nearest Neighbors (KNN). To enhance the interpretability of the models, SHAP values are used to explain the rationale behind the predictions made by the machine learning algorithms. By determining the influence of each feature on the model's predictions, SHAP values provide valuable insights into how various factors impact dew point temperatures. Identifying the most influential factors helps stakeholders understand the underlying processes affecting dew point temperature, enabling better-informed decisions and more effective operational strategies.

2. SHapley Additive exPlanations (SHAP)

The demand for eXplainable AI (XAI) systems is increasing as modern Machine Learning (ML) algorithms, especially deep learning models, become more powerful and complex, making it challenging to understand their behavior and why certain results or errors occur. Understanding these models is as crucial as their performance, as it fosters appropriate trust and reliance among users. Many machine learning models, such as Naive Bayes (NB), Logistic Regression (LR), and Decision Trees (DT), are inherently interpretable at a modular level. In contrast, while providing superior performance, deep learning (DL) models often lack interpretability in their predictions. Understanding the reasoning behind a model's decisions is crucial for building trust among users and stakeholders, ensuring that the model addresses issues securely and robustly. The lack of transparency in these "black-box" DL models is a key reason for their cautious adoption in many safety-critical sectors. Consequently, researchers are exploring various explainability methods to help users interpret the decisions of these complex models [14]. EXplainable AI (XAI) aims to make black-box models more comprehensible, accountable, and transparent to humans. This can be achieved by analyzing the model's overall decision-making process or focusing on specific outcomes [9]. XAI addresses challenges related to

transparency, interpretability, and explainability in complex models [15]. Transparency allows users to understand how a model makes decisions, contrasting with many models' "black-box" nature. Interpretability refers to the ability to comprehend the AI model's decisions by examining its internal workings. At the same time, explainability ensures that the outcomes of AI systems are presented in a way that is clear and understandable to users or experts [8].

It is necessary to explain these outcomes to enhance the reliability of AI decisions and predictions. Depending on the model's scope, explanations can be given on a local or global level.

Local explainability offers a straightforward and visual method to check how specific decisions were made, which should be provided whenever possible. Additionally, using intrinsically interpretable models, such as decision trees, can make the decision-making process easier to understand. Local explanation focuses on understanding how and why specific predictions are made individually, focusing on a limited number of instances. This approach is especially valuable when predictions are based on a few important features rather than complex relationships between all features [11].

Global explainability, on the other hand, aims to provide insight into the overall functioning of the model to ensure it does not make biased interpretations of the data. It aims to offer a comprehensive understanding of the entire model, identifying which features are most influential and exploring potential relationships between them on a larger scale [11]. Rather than focusing on specific decisions, global explainability helps uncover the model's broader logic, allowing machine learning practitioners to modify and improve its reasoning for more precise outcomes and quality [8].

SHapley Additive exPlanations (SHAP) is one of the most attractive XAIs, and it was developed based on game theory. In practical machine learning applications, clear model interpretability is often prioritized over maximizing accuracy. SHAP presents a visual, intuitive, and holistic framework that enhances the transparency of ensemble models, enabling clearer interpretation of the overall model while illustrating feature contributions at the observation level across any machine learning framework. SHAP can improve ensemble models by detecting outliers and missing values, aiding in variable selection, and identifying the root causes of performance issues. These capabilities increase the trustworthiness of ensemble models and promote their wider adoption [16].

SHAP values are based on Shapley values from game theory. Shapley values assess each player's impact on the game, quantifying the extent to which each feature influences the model's output. The contribution of an individual feature is determined by considering all possible combinations of features. Shapley values and the SHAP library serve as powerful tools for uncovering the insights hidden within a machine learning algorithm. SHAP utilizes Shapley values to explain local and global predictions [11]. Although calculating SHAP values can be computationally intensive for arbitrary machine learning models with unknown structures, efficient calculation methods have been developed for specific models, such as linear and decision tree-based models [17]. As a visualization tool, SHAP values enhance the transparency of a prediction model by offering a clear view of how it functions. The SHAP force visualization, in particular, provides an intuitive display of the features, making the results easily interpretable even for non-technical users [16].

SHAP offers interpretation with solid theoretical foundations and generalizes techniques proposed in several studies. In energy and power systems, SHAP has been used to explain long-term cooling energy consumption predictions, predict the efficiency of irregular dew point cooling systems [18], and benchmark building energy performance levels [12]. SHAP's applicability extends to various IoT domains, including environmental monitoring, finance, security, privacy, healthcare, and industrial applications [11]. SHAP has been employed in cybersecurity to explain and understand cybersecurity threats [10]. In healthcare, SHAP helps interpret models for accurate cardiac predictions [19], explain models for communicable disease prediction and sustainable living [20], and provide explainability for systems diagnosing and prognosing COVID-19 [21].

3. Research Framework

As illustrated in Figure 1, the research framework includes the following stages: Data Collection and Pre-Processing, Prediction Model, Model Evaluation and Selection, and Explainable Model. First, the air dryer dataset is collected from the IIoT system. Next, Exploratory Data Analysis (EDA) is performed to understand

the data comprehensively. The data is then transformed, cleaned, and split into training and testing datasets. The training dataset is used to train the prediction model. Once training is complete, the testing dataset is utilized for model evaluation. Subsequently, the top three models are selected for explainability analysis. SHAP is employed to provide both local and global explanations for the chosen models.

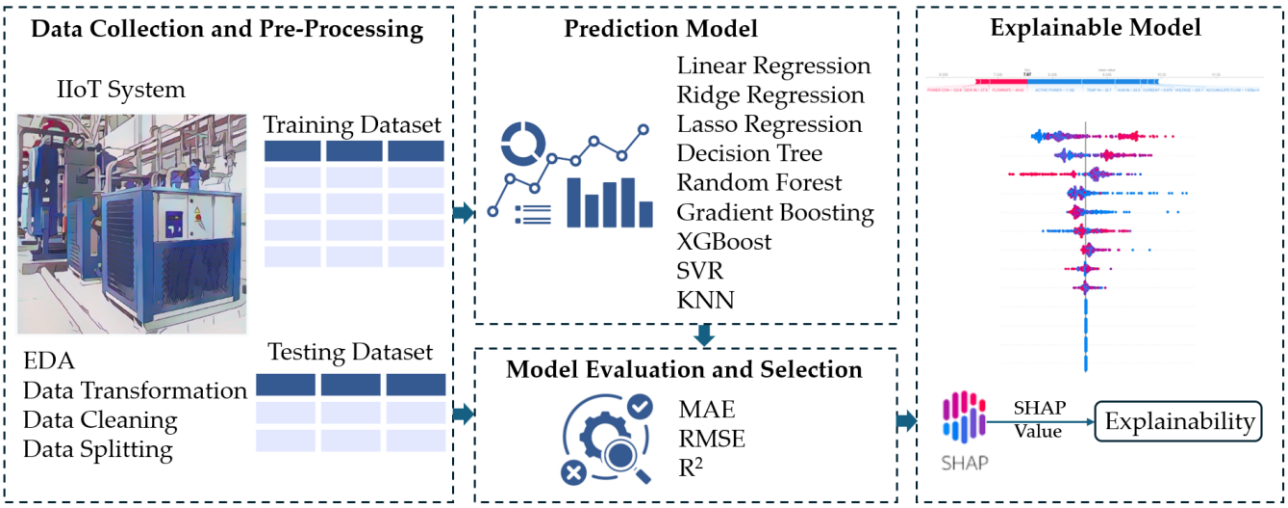


Figure 1. Research Framework

3.1 Data Collection and Pre-Processing

This paper's dataset for dew point prediction consists of sensor measurements collected through an IIoT system. These measurements, obtained from an air dryer machine, include 1,995 rows of data from 2022 and 2023. As shown in Table 1, the dataset includes several features used as independent variables to predict the dew point temperature (DEW OUT) in the predictive model. The data preprocessing steps include Exploratory Data Analysis, Data Transformation, Data Cleaning, and Data Splitting. These preprocessing steps significantly impact the predictive model's performance by ensuring the data is clean, consistent, and well-prepared for training.

3.1.1 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is conducted to comprehensively understand the data's distribution, relationships between variables, and overall data characteristics. Visualization tools and statistical methods derive insights that guide subsequent data preparation steps.

3.1.2 Data Transformation

The data is transformed and formatted to align with the requirements of the predictive model. This process includes normalizing numerical values to a uniform scale and ensuring that the data is fully compatible with the prediction model.

3.1.3 Data Cleaning

Data points that are irrelevant or redundant, such as duplicate records, irrelevant features, or outliers, are identified and eliminated to prevent them from adversely affecting the model's performance. During this process, features like "SN" and "DATE_STAMP" are excluded due to their lack of predictive value, and "TEMP OUT," "HUM OUT," and "PRESSURE OUT" are omitted as they are considered outputs or post-processed values. Additionally, constant features are identified and removed, as they provide no valuable information for the predictive model. These features include "CONDENSE TEMP," "CONDENSEHUM," "CONDENSEDEW," "COMPRESSOR STATUS," and "FANSTATUS."

Multicollinearity is addressed by computing a correlation matrix to identify highly correlated features. For example, strong correlations were observed between "TEMP IN" and "DEW IN" (correlation = 0.972) and

between "ACTIVE POWER" and "CURRENT" (correlation = 0.878). To mitigate this issue, the features "DEW IN" and "CURRENT" are removed to reduce multicollinearity and enhance model reliability.

3.1.4 Data Splitting

The data is segmented into training and testing sets with an 80:20 ratio. The training set is used for model development and training, while the testing set assesses the model's performance and validates its predictive accuracy.

Table 1. Features and Descriptions in the IoT System Dataset

Feature Name	Feature Description	Feature Type
SN	The serial number of the air dryer system that records the data.	Categorical
DATE_STAMP	The date and time when the data was recorded or measured are formatted as "day/month/year hour."	Date-Time
TEMP IN	The supply air temperature at which data is input into the device or system (unit: degrees Celsius).	Numerical
HUM IN	The supply air humidity level at which data is input into the device or system (unit: %).	Numerical
DEW IN	The dew point temperature at which data is input into the device or system (unit: degrees Celsius).	Numerical
TEMP OUT	The temperature at which data exits the device or system (unit: degrees Celsius).	Numerical
HUM OUT	The humidity level at which data exits the device or system (unit: %).	Numerical
PRESSURE OUT	The pressure at which data exits the device or system (unit: bar).	Numerical
FLOWRATE	The flow rate of the data (unit: liters/minute).	Numerical
ACCUMULATE FLOW	The accumulation or total value of the data (unit: liters/minute).	Numerical
VOLTAGE	The voltage used in the device or system (unit: volts).	Numerical
CURRENT	The current used in the device or system (unit: amps).	Numerical
ACTIVE POWER	The real-time power consumption of the system (unit: watts).	Numerical
CONDENSE TEMP	The temperature at which the moisture in the compressed air condenses in the device or system (unit: degrees Celsius).	Numerical
CONDENSEHUM	The humidity level in the condensed air after removing moisture (unit: %).	Numerical
CONDENSEDEW	The dew point of the condensed moisture removed from the air within the dryer (unit: degrees Celsius).	Numerical
POWER CON	The cumulative measure of energy usage over time (unit: kilowatt-hours).	Numerical
COMPRESSOR STATUS	The status of the compressor (1 for On, 0 for Off).	Categorical
FANSTATUS	The status of the fan (1 for On, 0 for Off)	Categorical

3.2 Prediction Models

This step uses the training dataset for model development and training. Various machine learning models are applied for dew point prediction, including Linear Regression, Ridge Regression, Lasso Regression, Decision Tree, Random Forest, Gradient Boosting, XGBoost, Support Vector Regressor (SVR), and k-Nearest Neighbors (KNN).

Linear Regression: A basic linear model that predicts a target variable as a linear combination of input features.

Ridge Regression: Ridge Regression is a technique used to address multicollinearity or high correlation among variables in regression analysis. While the coefficient estimates from Ridge Regression may be biased, they offer the advantage of reduced variance [22].

Lasso Regression: LASSO is a linear regression model that enhances prediction accuracy and interpretability by performing variable selection and applying regularization [23].

Decision Tree: A Decision Tree learns the hierarchical structure of data by iteratively partitioning the dataset into distinct branches, optimizing each split to maximize information gain. This process recursively decomposes the feature space into multiple subspaces [23].

Random Forest: An ensemble technique that creates several decision trees and combines their predictions to enhance accuracy and reduce the risk of overfitting. This technique effectively handles high-dimensional data without the need for feature selection. Furthermore, the independent subtrees within the RF can be trained in parallel, improving efficiency [23].

Gradient Boosting: Gradient boosting is commonly implemented using regression trees as its base learners. Unlike random forests, which utilize fully grown trees, gradient boosting generally relies on shallow trees with depths typically ranging from 1 to 5 [24].

XGBoost: XGBoost is an algorithm that leverages Gradient Boosting, making it more flexible and effective at handling complex tasks and non-linear relational data [23].

Support Vector Regressor (SVR): Support Vector Machine (SVM) is a popular classification technique recognized for its outstanding effectiveness in various scenarios. It is adjustable and can be employed to solve problems related to both classification and regression. In the context of regression, it is called Support Vector Regression (SVR). SVR aims to find the best hyperplane in a high-dimensional space that facilitates accurate predictions. Selecting the right parameters in SVR is essential, as it significantly influences the model's performance [25].

k-Nearest Neighbors (KNN): The K-Nearest Neighbors (KNN) regression model is a straightforward method that estimates the value of a new observation by utilizing the K most similar data points in the training dataset [26].

3.3 Model Evaluation and Selection

In this process, the algorithm for model evaluation and selection involves a systematic approach to comparing multiple regression models and selecting the best one based on performance metrics. The dataset is first preprocessed by scaling the features using StandardScaler to ensure that all features contribute equally to the model training. Tuning hyperparameters plays a crucial role in determining the performance of machine learning models, as they can perform differently depending on how their hyperparameters are initialized. Hyperparameter optimization for supervised learning models is a well-researched area, typically addressed by using an external accuracy measure or an objective function based on class labels (for classification tasks) or regression values (for regression tasks) [27].

For each model, hyperparameter tuning is performed using GridSearchCV with 5-fold cross-validation if the model has a predefined grid. This process aims to find the optimal set of hyperparameters that maximize the model's performance, measured by the R^2 score. For models without hyperparameters to tune, they are directly fitted on the scaled training data.

After fitting the models, various evaluation metrics—including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2—are calculated on the test data to assess each model's performance.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{3}$$

where y_i represents the actual value of a data point, $\hat{y}_i$ denotes the predicted value from a model, $\bar{y}$ It represents the mean of all values across the dataset, and n represents the total number of observations.

Based on the calculated metrics, the models are ranked, and the top three models with the best balance of high R^2, low MAE, and low RMSE are selected as the optimal models for predicting dew point.

3.4 Explainable Model

SHAP—a recent method for interpreting machine learning models—is applied to provide local and global explanations for the explainable model. SHAP values are employed to assess the importance of features within a model. To compute SHAP values, the following function is introduced [17]:

$$f_x(S) = f(h_x(z') = E[f(x)|x_S] \tag{4}$$

Where S represents the set of nonzero positions in the simplified feature representation z', and $E[f(x)|x_S]$ denotes the expected value of the function given the set S in the simplified feature space. SHAP values are derived by combining conditional expectations with the foundational Shapley values from game theory, ϕi, to each feature for i ranging from 1 to M [17]:

$$\emptyset_i = \sum_{i \in S \backslash \{i\}} [\frac{|S|!\,(M - |S| - 1)!}{M!} [f_x(S \cup \{i\}) - f_x(S)]] \tag{5}$$

4. Results and Discussion

This section presents the results of model evaluation and selection, explaining the performance of various machine learning models utilized in predicting dew point temperatures. It includes a comprehensive analysis of the models' accuracy and robustness. Additionally, the results of the Explainable Model are discussed, which include both local and global explanations. Local explanations focus on understanding the contribution of individual features to specific predictions, allowing for insights into how different factors interact to influence the output for particular instances. In contrast, global explanations provide a comprehensive overview of feature importance across the entire dataset, illustrating the broader trends and patterns the model has learned. A detailed discussion is provided to interpret these findings, focusing on both the predictive performance of the models and the implications of the explainability results.

4.1 Model Evaluation and Selection

The regression models were evaluated using a combination of hyperparameter tuning and cross-validation, then performance metrics were calculated on the test dataset. The evaluation considered multiple models, including Linear Regression, Ridge Regression, Lasso Regression, Decision Tree, Random Forest, Gradient Boosting, XGBoost, Support Vector Regressor (SVR), and k-Nearest Neighbors (KNN). A grid search was performed using 5-fold cross-validation to identify the best-performing configurations based on R^2 scores for models with tunable hyperparameters. In its basic form, Linear regression does not have hyperparameters, but variants, such as Ridge Regression and Lasso Regression, do include hyperparameters.

As shown in Table 2, the Ridge and Lasso Regression models yielded optimal results with an alpha value of 0.1. The Decision Tree model performed best without a maximum depth constraint (max_depth=None) and with a minimum of 5 samples required to split a node (min_samples_split=5). For the Random Forest model, the top configuration included 200 estimators (n_estimators=200), no maximum depth constraint, and a minimum of 2 samples required for splitting nodes. The Gradient Boosting model achieved the highest performance with a learning rate 0.2, a maximum depth of 5, and 200 estimators. Similarly, the XGBoost model's optimal setup featured a learning rate 0.2, a maximum depth of 5, and 200 estimators. The Support Vector Regressor (SVR) was best tuned with a cost parameter (C) of 100, an epsilon value of 0.5, and a radial basis function (rbf) kernel. Lastly, the k-Nearest Neighbors (KNN) model performed optimally with 3 neighbors (n_neighbors=3) and a distance weighting scheme.

Table 2. The details of hyperparameter tuning of each model

Model	Hyperparameter	Parameter List	Best Parameter
Linear Regression	-	-	-
Ridge Regression	alpha	[0.1, 1, 10, 100]	0.1
Lasso Regression	alpha	[0.1, 1, 10, 100]	0.1
Decision Tree	max_depth	[3, 5, 10, None]	None
	min_samples_split	[2, 5, 10]	5
Random Forest	n_estimators	[50, 100, 200]	200
	max_depth	[3, 5, 10, None]	None
	min_samples_split	[2, 5, 10]	2
Gradient Boosting	n_estimators	[50, 100, 200]	200
	learning_rate	[0.01, 0.1, 0.2]	0.2
	max_depth	[3, 5, 10]	5
XGBoost	n_estimators	[50, 100, 200]	200
	learning_rate	[0.01, 0.1, 0.2]	0.2
	max_depth	[3, 5, 10]	5
SVR	C	[0.1, 1, 10, 100]	100
	epsilon	[0.01, 0.1, 0.2, 0.5]	0.5
	kernel	['linear', 'poly', 'rbf']	rbf
KNN	n_neighbors	[3, 5, 10]	3
	weights	['uniform', 'distance']	distance

Table 3. presents the evaluation metrics for various regression models, highlighting their performance based on three key indicators: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2), along with their respective 95% confidence intervals (CI).

Table 3. The evaluation results.

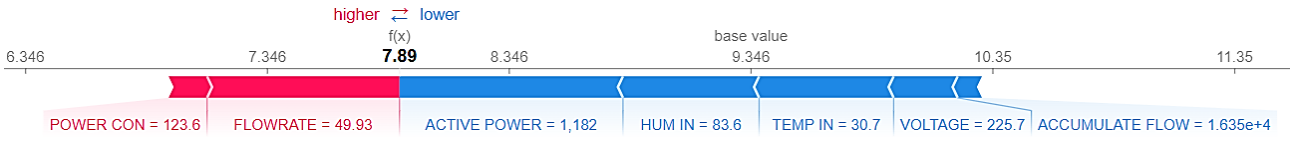
Model	MAE (95% CI)	RMSE (95% CI)	R^2 (95% CI)
Linear Regression	1.751 (1.602–1.933)	2.434 (2.192–2.681)	0.443 (0.350–0.529)
Ridge Regression	1.750 (1.600–1.932)	2.433 (2.190–2.680)	0.443 (0.350–0.529)
Lasso Regression	1.713 (1.560–1.888)	2.408 (2.169–2.661)	0.455 (0.369–0.537)
Decision Tree	0.415 (0.339–0.505)	0.957 (0.733–1.181)	0.914 (0.869–0.948)
Random Forest	0.350 (0.279–0.425)	0.821 (0.615–1.033)	0.937 (0.900–0.965)
Gradient Boosting	0.371 (0.298–0.458)	0.863 (0.618–1.122)	0.930 (0.881–0.964)
XGBoost	0.399 (0.329–0.483)	0.870 (0.653–1.104)	0.929 (0.887–0.960)
SVR	2.368 (2.202–2.551)	3.008 (2.833–3.208)	0.150 (0.087–0.204)
KNN	1.248 (1.098–1.418)	2.027 (1.782–2.295)	0.614 (0.519–0.696)

MAE measures the average magnitude of errors between predicted and actual values, with lower values indicating better performance. RMSE, which also reflects the average error magnitude but gives more weight to larger errors, similarly benefits from lower values. η indicates the proportion of variance in the target variable that the model can explain, with higher values suggesting better performance. Among the models evaluated, Random Forest emerged as the top performer, with the lowest MAE and RMSE values and the highest R^2 score, explaining approximately 93.7% of the variance in the data. This indicates that Random Forest is the most accurate model in this comparison. Gradient Boosting and XGBoost also performed well, with slightly higher errors and R^2 values that indicate they explain around 93.0% and 92.9% of the variance, respectively. These three models—Random Forest, Gradient Boosting, and XGBoost—are the best-performing models in this evaluation, making them the top options for accurate prediction based on this dataset.

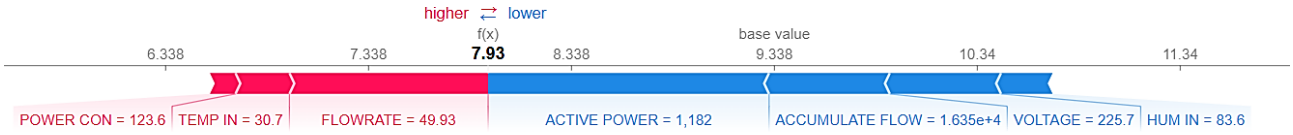
4.2 Explainable Model

4.2.1 Local Explanations

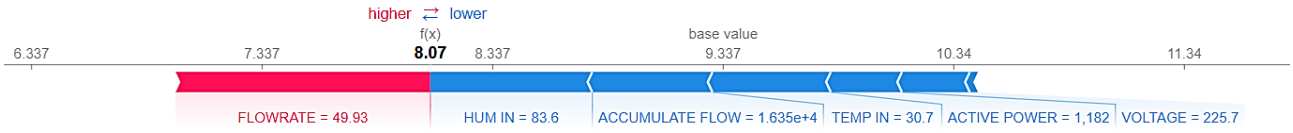
Local interpretability involves explaining the attributes and reasoning behind a specific individual data point instead of examining overall trends or patterns. This approach aims to improve the understanding of the factors that influence a specific outcome or prediction, assisting in sophisticated data analysis and comprehending unique situations. For Local explanation, Figure 2 depicts SHAP (SHapley Additive exPlanations) force plots for the top three different machine learning models from the evaluation results: Random Forest (RF), Gradient Boosting (GB), and XGBoost (XGB). These plots illustrate the contribution of various features to the prediction for the 20th instance in the dataset. In each plot, the base value represents the mean prediction across the training data, and the specific prediction for this instance (f(x)) deviates from the base value based on the influence of different features. Features pushing the prediction higher are shown in red, while those reducing the prediction are displayed in blue.



(a) RF



(b) GB



(c) XGB

Figure 2. Local explanation by SHAP for the 20th instance

For the RF model, the predicted value is 7.89. The most significant features pushing the prediction higher are "FLOWRATE" and "POWER CON," while features such as "ACTIVE POWER" and "HUM IN" reduce the prediction. The GB model produces a slightly higher predicted value of 7.93. Key contributors to the increase include "FLOWRATE," "TEMP IN," and "POWER CON," while features such as "ACTIVE POWER," "ACCUMULATE FLOW," and "VOLTAGE" reduce the prediction. In comparison, the XGB model produces the highest prediction of 8.07, with the feature "FLOWRATE" having the most significant positive impact, pushing the prediction upwards. Conversely, features such as "HUM IN," "ACCUMULATE FLOW," "TEMP IN," and "ACTIVE POWER" reduce the prediction. Overall, while all three models identify similar features as influential in predicting the dew point, their contributions vary slightly across the models, resulting in different prediction values.

4.2.2 Global Explanations

Global interpretability involves understanding an ML model's behavior and performance across the entire dataset. Figure 3 shows three SHAP (SHapley Additive exPlanations) plots representing the global explanation of the feature importance for different machine learning models: Random Forest (RF), Gradient Boosting (GB), and XGBoost (XGB). These models are used to predict dew points based on a set of features, and SHAP values are utilized to interpret how much each feature contributes to the predictions. Across all

three models, "ACTIVE POWER" appears to be an important feature, as each plot has significant SHAP values. However, the distribution of SHAP values varies slightly, corresponding to the different learning methods employed by each algorithm.

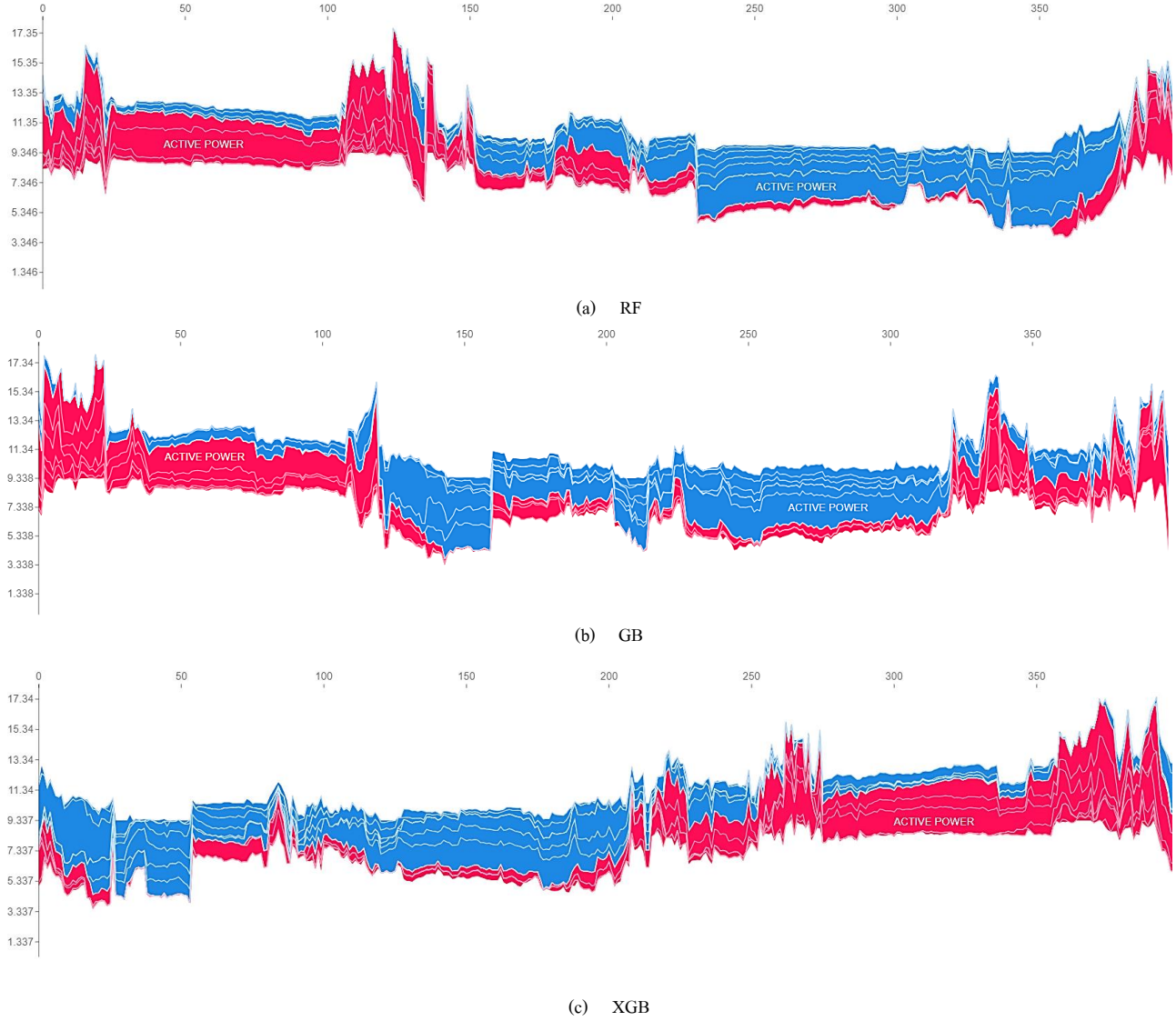


Figure 3. Global explanation by SHAP for all instances

Figure 4 displays SHAP summary plots illustrating the global explanation of feature importance for three machine learning models: Random Forest (RF), Gradient Boosting (GB), and XGBoost (XGB). These plots use SHAP values to interpret the predictions of each model. For Random Forest (RF) and XGBoost (XGB), the most influential features are "ACTIVE POWER," "TEMP IN," and "HUM IN," respectively. In contrast, for Gradient Boosting (GB), the key contributing factors are "ACTIVE POWER," "HUM IN," and "TEMP IN," respectively.

Across all models, "ACTIVE POWER", "TEMP IN", and "HUM IN" appear to have the most significant impact on the dew point. The pattern of their influence varies slightly, indicating the unique learning mechanisms of each model.

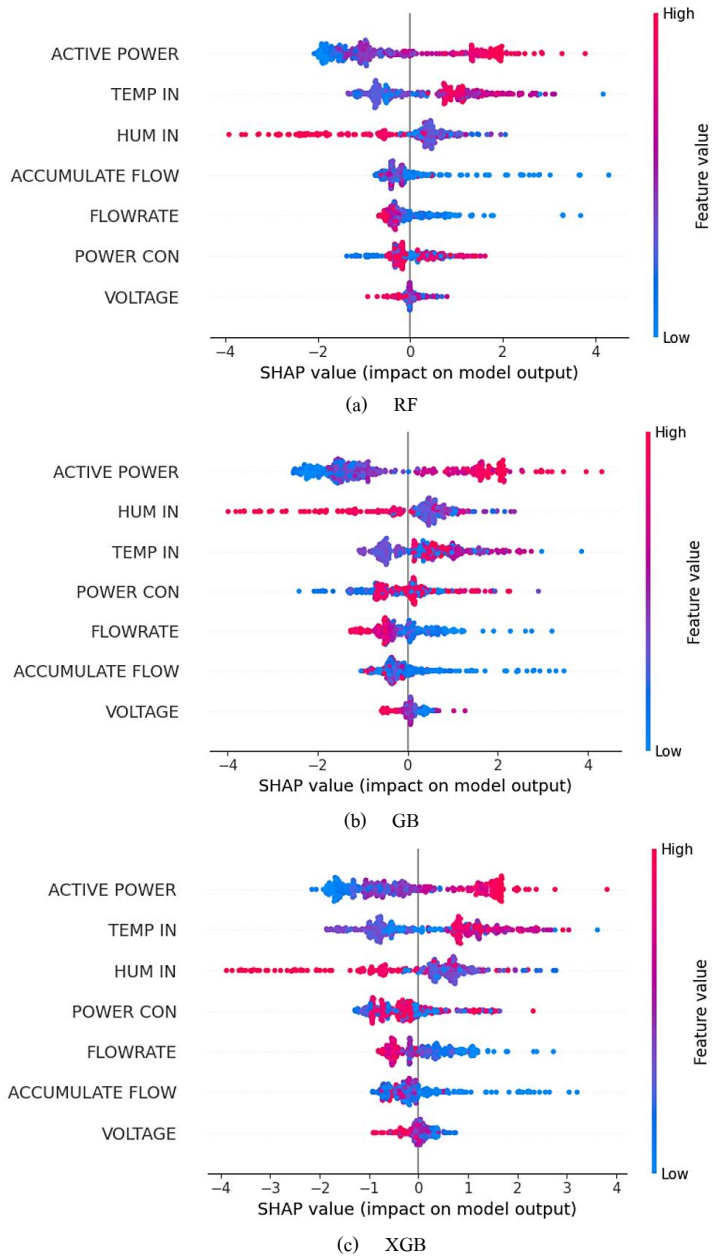


Figure 4. Global explanation by SHAP: Summary plot

4.3 Discussion

According to the results, the Random Forest model achieved the lowest MAE (0.350) and RMSE (0.821) and the highest R^2 (0.937), indicating its superior accuracy and ability to explain the variance in the data. Similarly, Gradient Boosting and XGBoost also demonstrated strong performance with high R^2 values (0.930 and 0.929, respectively). These findings align with the study in [3], which also emphasizes the effectiveness of Random Forest (RF) and Gradient Boosting Decision Tree (GBDT) in achieving high R^2 and low RMSE. This is consistent with the results from [6], where the Random Forest Regressor was the most accurate predictor in modeling the heatwave index across various machine learning models. The superior performance of these models can be explained by their ability to uncover complex, non-linear relationships within the dataset. Random Forest, as an ensemble method, reduces overfitting by averaging multiple decision trees, which enhances its generalization capability. Gradient Boosting and XGBoost, both boosting methods, improve predictive performance by sequentially correcting errors of previous models, which allows them to achieve high accuracy even in the presence of complex interactions between features.

In contrast, the Support Vector Regressor (SVR) delivered the poorest performance, with the highest RMSE (3.008) and lowest R^2 (0.150). This finding is inconsistent with [3], which indicated that SVR achieved the highest accuracy in predicting dew-point temperature. The underperformance of SVR in this case may be attributed to its limitations, particularly its difficulty in capturing complex, non-linear relationships within the data. Moreover, the performance of SVR is significantly impacted by how well the parameters are configured [25]. If hyperparameters are not optimally tuned, SVR may struggle to capture the underlying complexities of dew point prediction, resulting in lowered predictive performance. The selection of appropriate learning parameters is crucial for the model's learning performance and generalization ability, directly impacting prediction accuracy [28].

Combining SHAP (SHapley Additive exPlanations) values has enhanced our understanding of model behavior. SHAP values show that the real-time power consumption of the system ("ACTIVE POWER"), supply air temperature ("TEMP IN"), and supply air humidity ("HUM IN") are important features influencing dew point predictions. SHAP's local and global interpretability has clarified how different features impact model predictions and indicates differences in feature importance across models. The results from SHAP analysis offer significant potential for improving operational efficiency and safety in industrial environments where dew point control is crucial. For instance, precise dew point management in electronics manufacturing can prevent product defects and equipment malfunctions, leading to higher production quality and reduced downtime. Similarly, in precision engineering, effective dew point control can mitigate corrosion and material degradation issues. By applying these insights, industries can develop more effective strategies for monitoring and controlling environmental conditions, ultimately enhancing operational outcomes and safety.

5. Conclusions

This research has demonstrated the performance of several machine learning models in predicting dew point temperatures using data from an Industrial Internet of Things (IIoT) system. The evaluation of models including Ridge Regression, Lasso Regression, Decision Tree, Random Forest, Gradient Boosting, XGBoost, Support Vector Regressor (SVR), and k-Nearest Neighbors (KNN) highlights the strengths of ensemble methods. Random Forest emerged as the top performer with the lowest MAE and RMSE values and the highest R^2 score, indicating its robustness in capturing the complex patterns in the data. Gradient Boosting and XGBoost also performed well, reflecting the effectiveness of boosting techniques in refining predictions.

The top three models—Random Forest, Gradient Boosting, and XGBoost—are used for explainability analysis with SHAP (SHapley Additive exPlanations). According to the SHAP results, the system's real-time power consumption ("ACTIVE POWER") is the most influential factor in dew point predictions for all three models. Supply air temperature ("TEMP IN") is the second most influential factor for Random Forest and XGBoost and the third most influential for Gradient Boosting. Supply air humidity ("HUM IN") is the second most influential factor for Gradient Boosting and the third most influential for Random Forest and XGBoost. The local and global interpretability provided by SHAP values has clarified how different features impact model predictions and explained the variations in feature importance across the different algorithms.

The findings indicate the importance of selecting the appropriate model for accurate dew point predictions and the value of using interpretability tools like SHAP to understand model behavior. By leveraging Random Forest, Gradient Boosting, and XGBoost and applying SHAP values for model interpretability, stakeholders can make more informed decisions regarding dew point control, ultimately leading to enhanced safety, quality, and efficiency in industrial processes.

The study contributes to existing knowledge by emphasizing the effectiveness of advanced machine learning models in dew point prediction and demonstrating the efficiency of SHAP for model interpretability. However, the study's limitations include its reliance on a specific dataset, which may impact the generalizability of the findings to other industrial settings or environmental conditions. Future research could focus on expanding the dataset and incorporating additional features. Investigating deep learning models, such as LSTM and Transformer architectures, could significantly improve predictive performance. Real-time prediction scenarios and uncertainty quantification methods could enhance reliability and practical applicability. Additionally, analyzing feature interactions and time series could uncover complex dependencies and better capture historical trends. Furthermore, external datasets should be validated to strengthen the model's generalizability.

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