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Review Article

Hybrid Model for Forecasting Temperature in Khartoum Based on CRU data

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ABSTRACT

This consider leverages verifiable climatic data from the Climatic Research Unit (CRU), traversing from 1901 to 2022, to create progressed temperature forecasting models for Khartoum, Sudan. By applying state-of-the-art machine learning techniques, including Hybrid model, we aim to progress the precision of temperature forecasts in a semi-arid climate. The integration of long-term CRU data permits for the recognizable proof of climate patterns and patterns, upgrading the unwavering quality of short- and long-term forecasts. Moved forward temperature forecasting can altogether advantage basic segments empowering way better adjustment to climatic changes and extraordinary climate occasions. Our approach illustrates the potential of combining authentic climate data with machine learning to supply noteworthy experiences for climate flexibility.

1. INTRODUCTION

Khartoum, the capital of Sudan, encounters a semi-arid climate that brings approximately critical temperature changes and meager precipitation all through the year. This climatic instability postures basic challenges for divisions such as horticulture, wellbeing, and vitality administration, subsequently requiring the improvement of exact temperature estimating models to moderate potential antagonistic impacts.

The semi-arid climate of Khartoum is characterized by hot summers and mellow winters, with temperature extremes regularly driving to inconvenient impacts on agribusiness and human wellbeing. Agrarian exercises, which frame a significant portion of the neighborhood economy, are especially defenseless to these temperature varieties. Viable temperature determining can hence help in optimizing rural hones, making strides trim yields, and guaranteeing nourishment security [1,2,3,4,5].

In later years, progressions in meteorological innovation, coupled with the expansion of machine learning (ML) and artificial intelligence (AI) methods have revolutionized climate expectation models. These advanced models use broad datasets, counting authentic climate records, adj. symbolism, and real-time sensor data, to predict temperature varieties with exceptional precision. Thinks about have appeared that AI and ML models outflank conventional statistical strategies in temperature forecasting, giving more dependable and significant bits of knowledge [6,7,8,9,10].

AI and ML models have been effectively connected in different climatic districts, illustrating their viability in improving the accuracy of temperature forecasts. For occasion, deep learning models, such as convolutional neural systems (CNNs) and repetitive neural systems (RNNs), have been utilized to predict climate designs and temperature inconsistencies with tall

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exactness [11,12,13,14,15]. These models can distinguish complex patterns and relationships in expansive datasets that are frequently ignored by customary strategies.

The integration of satellite imagery into temperature forecasting models has advance improved prediction precision. Satellite data gives comprehensive and high-resolution scope of atmospheric conditions, empowering point by point examination of temperature patterns and irregularities [16,17,18,19,20]. When combined with ground-based perceptions, this data offers a vigorous establishment for creating exact temperature forecasting models custom-made to particular districts, including Khartoum.

Additionally, the application of AI in temperature forecasting can altogether help in planning for extraordinary climate occasions, such as heat waves. The recurrence and escalated of warm waves have been on the rise due to worldwide climate alter, posturing serious dangers to open wellbeing and framework. Precise temperature forecasts can encourage convenient intercessions, such as issuing warm notices, mobilizing crisis administrations, and executing cooling techniques in urban ranges [21,22,23].

Agriculture in Sudan, intensely dependent on climatic conditions, can advantage gigantically from exact temperature figures. These estimates can optimize planting and gathering plans, decrease the chance of edit disappointment, and improve water asset administration. By anticipating temperature patterns, agriculturists can make educated choices on water system, bug control, and other basic rural exercises [18]-[19].

In expansion to farming, precise temperature forecasts are imperative for vitality administration in Khartoum. The request for vitality, especially power for cooling amid hot periods, is closely connected to temperature varieties. Dependable figures can offer assistance in overseeing vitality supply and request, lessening the chance of control blackouts, and upgrading the proficiency of vitality dissemination frameworks [16]-[23].

This consider points to create a vigorous temperature forecasting demonstrate for Khartoum by leveraging progressed data analytics methods, counting machine learning and adherent symbolism. The objective is to supply exact and convenient temperature figures that can support different divisions within the city, subsequently improving nearby capacity for climate forecast and climate versatility. The results of this inquire about are anticipated to contribute essentially to moderating the impacts of climate changeability and progressing the quality of life in Khartoum.

The mean objective from our work is to upgrade temperature forecasting for Khartoum utilizing progressed machine learning strategies. By applying models such as Hybrid SVM-RF Method to verifiable climate data, we point to move forward expectation accuracy for temperature fluctuations.

2. RELATED WORK

Exact temperature forecasting is pivotal for overseeing different segments influenced by climatic conditions. A significant body of inquire about has investigated distinctive strategies and innovations for moving forward temperature forecast accuracy.

Early temperature forecasting models essentially depended on factual methods and linear regression approaches. For occasion, statistical models such as autoregressive coordinates moving normal (ARIMA) have been broadly utilized for time-series forecasting of temperature [24]. These models are foundational but frequently need the accuracy required for exceedingly energetic and complex climate patterns.

Advancements in machine learning (ML) and artificial intelligence (AI) have essentially upgraded temperature forecasting capabilities. For case, support vector machines (SVMs) and choice trees have been connected to climate forecast errands, illustrating progressed accuracy over conventional statistical strategies [25], [26]. Moreover, outfit strategies like Random Forests combine different models to improve expectation execution [27].

Deep learning methods, especially convolutional neural networks (CNNs) and repetitive neural networks (RNNs), have appeared guarantee in climate determining. CNNs are proficient at taking care of spatial data from satellite images, whereas RNNs, counting Long Short-Term Memory (LSTM) networks, are compelling in capturing transient conditions in climate information [28], [29]. These methods have been utilized to demonstrate and predict temperature varieties with higher accuracy [30].

Integration of satellite data with machine learning models has been investigated to make strides forecasting accuracy. Satellite perceptions give comprehensive spatial scope and high-resolution data, which can be utilized in conjunction with ML algorithms to refine temperature forecasts [31], [32]. Studies have highlighted the viability of combining satellite data with ground-based measurements for improved forecasting [33].

In later a long time, hybrid models that coordinated AI with physical climate models have picked up consideration. These models combine the qualities of numerical climate forecast (NWP) models with machine learning procedures to improve forecast accuracy [34], [35]. Such approaches use the strength of physical models and the adaptability of ML calculations.

Investigate particular to semi-arid and bone-dry locales, such as Sudan, has moreover been conducted. Thinks about in comparative climatic conditions have illustrated the appropriateness of progressed determining methods in overseeing agrarian and water assets [36], [37]. For occasion, temperature forecasting models custom fitted for parched regions offer assistance optimize water system plans and oversee heat stress in crops [38].

Additionally, the effect of climate change on temperature extremes has been a critical region of research. Climate models and forecasts are progressively centering on anticipating extraordinary climate events, including warm waves, which are getting to be more visit and serious due to worldwide warming [39], [40]. These thinks about emphasize the require for precise forecasting to relieve the impacts of extraordinary temperatures on wellbeing and foundation.

Later improvements in AI and big data analytics have presented modern strategies for climate forecasting. Strategies such as deep support learning and generative adversarial networks (GANs) are being investigated for their potential to show complex climate frameworks and make strides figure unwavering quality [41], [42]. These developing innovations offer promising roads for future research in temperature forecasting.

Lastly, the application of temperature forecasting models in urban situations has been considered to address challenges such as warm island impacts and vitality utilization [43][44]. These models help in urban arranging and management by giving precise temperature forecasts that offer assistance relieve the impacts of extraordinary warm in densely populated ranges.

3. DATA AND METHODOLOGY

3.1 CRU Data

In this work, CRU (Climatic Research Unit) data available from 1901 to 2022 were utilized to move forward temperature forecasting models in Khartoum. CRU data may be a wealthy and comprehensive source of historical climate data, permitting us to analyze long-term patterns and identify climate patterns. Utilizing machine learning methods, we are ready to prepare this big data and create exact temperature forecasting models. This approach helps progress the exactness of short- and long-term forecasts in Khartoum. With these more precise estimates, way better choices can be made to adjust to climate inconstancy and reduce its negative impacts.

3.2 Hybrid SVM-RF Method

The Hybrid SVM-RF strategy is a gathering learning method that combines the qualities of Support Vector Machines (SVM) and Random Forest (RF) to progress prescient precision and show vigor. The taking after steps diagrams the method included in developing and utilizing the Crossover SVM- RF show:

1. **Data Preparation**

Before training the Hybrid SVM-RF demonstrate, the data is preprocessed and part into preparing and testing sets. The information is at that point normalized to guarantee that all highlights contribute similarly to the models expectations.

2. **Training the SVM Model**

The SVM show is trained on the preparing data utilizing the Radial Basis Function (RBF) part. The optimization of the SVM model includes selecting the leading regularization parameter C and the part coefficient γ through framework look and cross-validation. The choice work for the SVM is given by:

$$f_{\text{SVM}}(x) = \sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b \quad (1)$$

Where αi the support vectors, yi are the target values are, K(xi,x) is the RBF kernel function and b is the bias term.

3.3 Training the Random Forest Model

At the same time, a Random Forest model is trained on the same preparing information. The Random Forest model comprises of an outfit of choice trees. The optimization includes selecting the most excellent number of trees ($n\_estimators$) and the most extreme profundity of the trees (max_depth) through framework look and cross- approval. The forecast work for the Random Forest is given by:

$$f_{\text{RF}}(x) = \frac{1}{T} \sum_{t=1}^{T} h_t(x) \quad (2)$$

Where T is the number of trees and ht(x) is the prediction of the t-th tree.

3.4 Combining Predictions

The forecasts from the SVM and RF models are combined employing a stacking approach. The forecasts of both models are utilized as input highlights for a meta-learner show, ordinarily
A straight relapse show. The meta-learner is trained to memorize the ideal combination of the base model forecasts. The combined forecast is given by:

$$f_{\text{Hybrid}}(x) = w_{\text{SVM}} f_{\text{SVM}}(x) + w_{\text{RF}} f_{\text{RF}}(x) + b_{\text{meta}} \quad (3)$$

Where wSVM and wRF are the weights learned by the meta-learner, and bmeta is the bias term.

3.5 Meta-Learner Training

The meta-learner show is prepared on the combined forecasts from the preparing set. This model learns the ideal weights for the SVM and RF forecasts, viably leveraging the qualities of both models to create a last forecast.

3.6 Making Predictions

After preparing the meta-learner, the Hybrid SVM-RF models can be utilized to create Forecasting on unused data. The method includes creating predictions from both the SVM and RF models and after that combining these forecasts utilizing the prepared meta-learner show.

3.7 Evaluation

The execution of the Hybrid SVM-RF show is assessed utilizing different measurements such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-Squared. These measurements offer assistance in evaluating the accuracy and strength of the show.
The figure A outlines the engineering of the Hybrid SVM-RF model. It starts with the input data, which is bolstered into both the SVM model and the Arbitrary RF. The SVM show creates SVM forecasts, whereas the model RF produces forecasts. These forecasts are at that point combined and utilized as input highlights for a meta-learner model. The meta-learner model forms these combined forecasts to create the ultimate forecast. This design leverages the qualities of both the SVM and RF models to improve generally prescient accuracy.

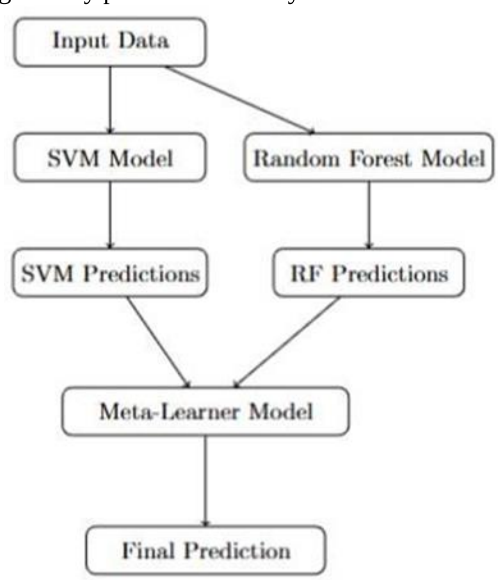

Fig .1. Hybrid SVM-RF Model Architecture.

This point by point parameter setup gives understanding into how each model is fine-tuned to realize ideal execution for temperature modeling in Khartoum. Understanding these parameters makes a difference in comprehending the trade-offs made amid the show preparing prepare to adjust complexity, execution, and computational proficiency.

TABLE I. BEST PARAMETERS FOR MACHINE LEARNING MODELS FOR DEMONSTRATING TEMPERATURE IN KHARTOUM.

Model	Best Parameters
SVM	C= 1 Gamma = scale Kernel= rbf
Random Forest	Max depth = None Min samples split =: 5 N estimators = 100
Hybrid SVM-RF	C = 1 Gamma = scale Kernel = rbf max depth = None min samples split = 5 n estimators = 100

4. RESULTS AND DISCUSSION

The table 1 presents the ideal hyper parameters for three diverse models: SVM, RF, and a Hybrid SVM-RF models.
For the SVM model, the taking after parameters are utilized:

- The C parameter is set to 1. This regularization parameter controls the trade-off between accomplishing a low error on the training data and minimizing the standard of the weights, which makes a difference avoid over fitting.
- The gamma parameter is set to 'scale'. This part coefficient determines the impact of a single preparing case, with 'scale' utilizing $\frac{1}{(n\_\text{features} \times X.var(O)}$.
- The kernel parameter is set to 'RBF' (Radial Basis Function), a popular kernel sort that maps input space into higher-dimensional space to handle non-linear connections.

For the RF, the taking after parameters are utilized:

- max_depth is set to None, which implies hubs are extended until all takes off contain less than the minimum number of tests required to split. This parameter controls the maximum depth of the tree, influencing model complexity.
- min_samples_split is set to 5, indicating the minimum number of tests required to split an internal node, subsequently controlling the measure of the tree and making a difference to maintain a strategic distance from overfitting.
- n_estimators is set to 100, indicating the number of trees within the forest. Expanding the number of trees can make strides show execution but too increases computational taken a toll.

For the Hybrid SVM-RF model, which combines both SVM and RF approaches, the taking after parameters are utilized:

- SVM Parameters:
- C is set to 1.
- gamma is set to 'scale'.
- kernel is set to 'rbf'.
- Random Forest Parameters:
- max_depth is set to 10.
- min_samples_split is set to 5.
- n_estimators is set to 100.

The table 2 presents the execution measurements for three diverse models: SVM, RF, and Hybrid SVM-RF. The measurements include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE %), and R-Squared.
For the SVM models, the MSE is 1.6604, RMSE is 1.2886, MAE is 1.0185, MAPE is 3.4230%, and R-Squared is 0.87982. The RF model shows an MSE of 1.5639, RMSE of 1.2506, MAE of 0.9547, MAPE of 3.2656%, and an R-Squared esteem of 0.8868. The Hybrid SVM-RF model illustrates the excellent execution with an MSE of 1.4322, RMSE of 1.1968, MAE of 0.9306, MAPE of 3.1674%, and an R-Squared value of 0.8963.
These results show that the Hybrid SVM-RF model outflanks both the SVM and RF models, as prove by its lower values in MSE, RMSE, MAE, and MAPE %, and higher R- Squared value. Lower MSE, RMSE, MAE, and MAPE % values demonstrate way better forecast accuracy, while a better R-Squared value recommends a better better; a much better;a higher;a stronger;an improved">a higher fit of the model to the data. This detailed mistake matrix gives important experiences into the comparative adequacy of these machine learning models in foreseeing temperature in Khartoum.

TABLE II. ERROR MATRIX FOR TESTING DATA FOR TEMPERATURE IN KHARTOUM UTILIZING MACHINE LEARNING MODELS.

Model	MSE	RMSE	MAE	MAPE %	R-Squared
SVM	1.6604	1.2886	1.0185	3.4230	0.87982
Random Forest	1.5639	1.2506	0.9547	3.2656	0.8868
Hybrid SVM-RF	**1.4322**	**1.1968**	**0.9306**	**3.1674**	**0.8963**

Figure 2 outlines the comparison between the initial temperature data and the forecasts made by the SVM model, along side future forecasts. The black line represents the first data, showing the actual temperature values over time. The blue line delineates the model forecasts made by the SVM show, and the ruddy dashed line represents the longer term forecasts made by the model.

The graph shows that the SVM model closely follows the pattern of the initial information, showing its viability in capturing the basic drift and seasonality within the temperature data. The future forecasts give a continuation of the models trend, offering understanding into expected future temperatures. This visualization makes a difference in understanding the models execution and its capacity to generalize past the training data.

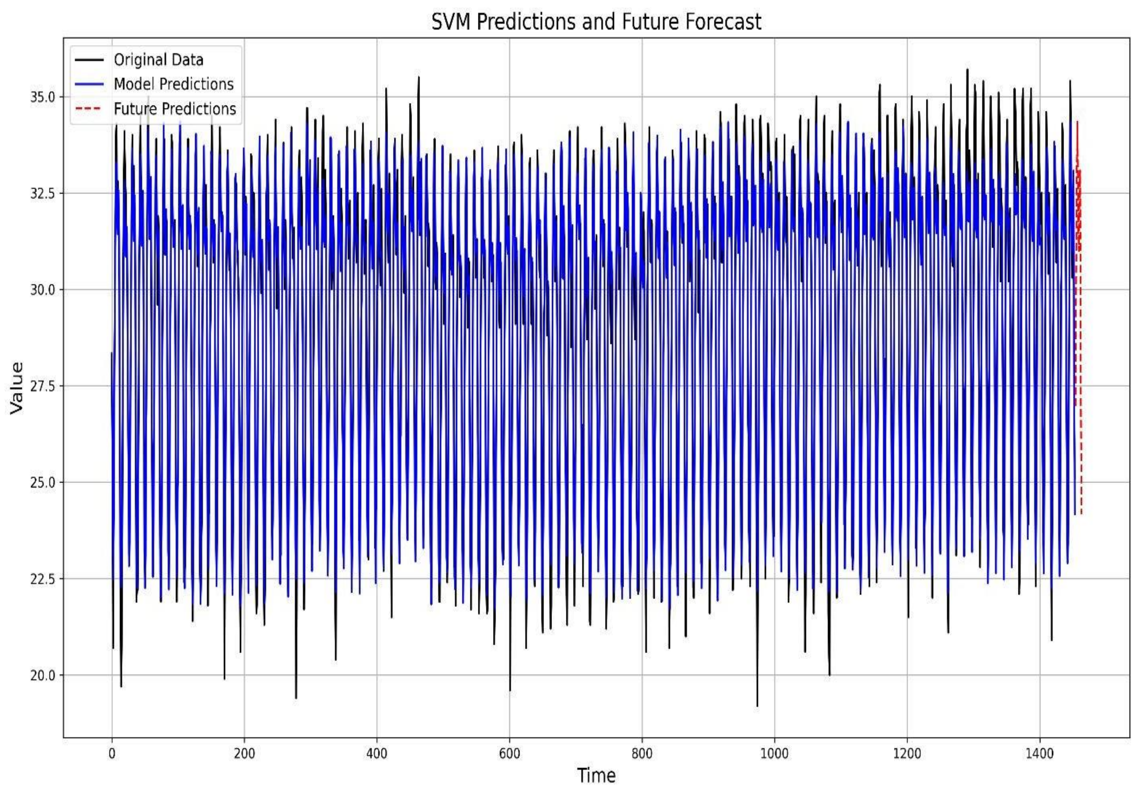

Fig .2. Modelling Temperature in Khartoum using SVM Model.

Figure 3 outlines the comparison between the initial temperature data and the forecasts made by the RF model, along with future forecasts. The black line represents the first data, showing the actual temperature values over time. The blue line depicts the model forecasts made by the RF, and the red dashed line represents long-term forecasts made by the model.

The chart shows that the RF model closely takes after the pattern of the first data, showing its adequacy in capturing the basic trend and seasonality within the temperature data. The longer-term forecasts give a continuation of the models trend, advertising knowledge into expected future temperatures. This visualization makes a difference in understanding the models execution and its capacity to generalize past the preparing data.

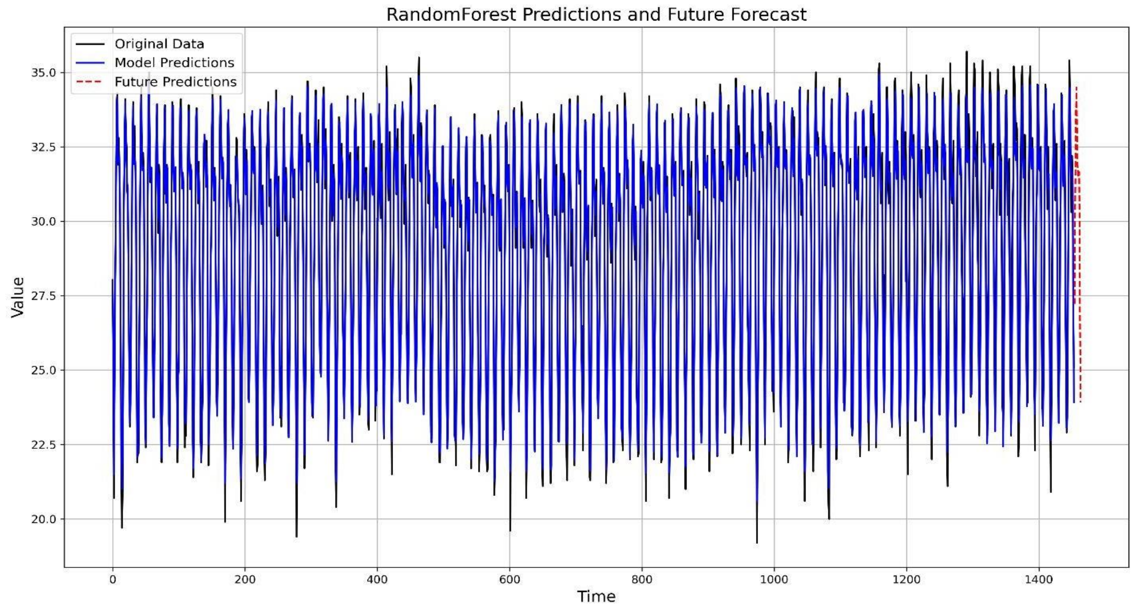

Fig .3. Modelling Temperature in Khartoum using Random Forest Model.

Figure 4 outlines the comparison between the original temperature data and the forecasts made by the Hybrid SVM-RF show, together with future estimates. The black line represents the first data, appearing the real temperature values over time. The blue line delineates the model forecasts made by the Hybrid SVM-RF model, and the red dashed line represents the future forecasts made by the model.

The graph appears that the Hybrid SVM-RF show closely takes after the pattern of the first data, demonstrating its viability in capturing the basic trend and seasonality within the temperature data. Long haul forecasts give a continuation of the models trend, advertising understanding into expected future temperatures. This visualization makes a difference in understanding the models execution and its capacity to generalize past the training data.

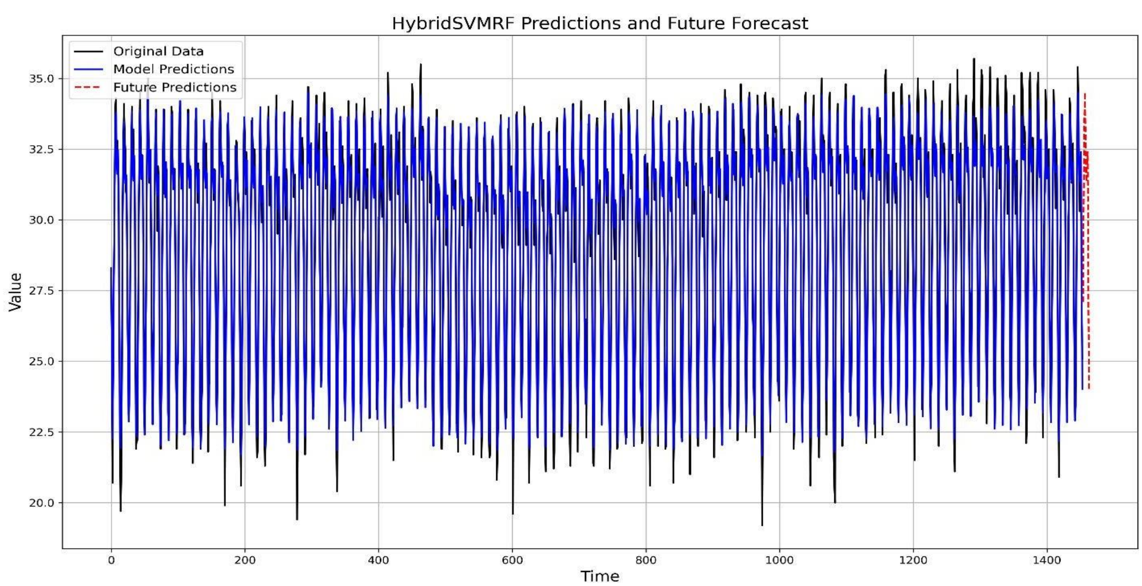

Fig .4. Modelling Temperature in Khartoum using Hybrid SVM-RF Model.

Table 3 gives the predicted temperatures for Khartoum from January 2023 to October 2023. The forecasts are produced utilizing three distinctive models: SVM, RF and Hybrid SVM-RF. Each column represents the forecasts from one of these models for each month within the indicated period.

The SVM models predictions are recorded within the second column. SVM is known for its viability in handling non-linear connections in data through the utilize of kernel functions. For occurrence, in January 2023, the SVM model predicts a temperature of 26.9771 degrees Celsius.
The RF models forecasts are appeared within the third column. This model is an outfit learning method that works by constructing different choice trees amid training and outputting the mean forecast of the individual trees. For January 2023, the RF model predicts a temperature of 27.2190 degrees Celsius.
The fourth column shows the forecasts from the Hybrid SVM-RF show, which combines the qualities of both the SVM and RF models to progress forecast accuracy. This hybrid approach points to use the SVM capacity to model complex, non-linear connections and the RF strength and high accuracy. For January 2023, the Hybrid SVM-RF model predicts a temperature of 27.0919 degrees Celsius.
This comparative table allows for a simple evaluation of the diverse models forecasting capacities over the desired period. It is clear from the forecasts that whereas each model has its possess strengths, the Hybrid SVM-RF show points to supply a more adjusted and exact figure by combining the preferences of both the SVM and RF models.

TABLE III. FORECASTING TEMPERATURE IN KHARTOUM USING MACHINE LEARNING MODELS.

Date	SVM	Random Forest	Hybrid SVM-RF
January, 2023	26.97712294	27.21898571	27.09192169
February, 2023	30.47869405	31.05171746	30.82627613
March, 2023	33.09462296	33.62738175	33.4810644
April, 2023	34.33883764	34.49297937	34.50756667
May, 2023	31.86836784	32.17304802	32.12192856
June, 2023	30.99798836	31.63399035	31.33558787
July, 2023	32.31862603	31.49981429	32.0043438
August, 2023	33.07802412	31.65391825	32.40028795
September, 2023	27.57714196	27.47861587	27.65014152
October, 2023	24.16539696	23.91689084	24.0113851

Figure 5 presents a comparative analysis of temperature forecasts for Khartoum utilizing three diverse machine-learning models: SVM, RF and Hybrid SVM-RF. The x-axis show the months from January 2023 to October 2023 and the y-axis represent the predicted temperature values.
SVM: The blue line represent the temperature forecasts made by the SVM model. The forecasts appear a moderately steady trend with minor vacillations over the foretasted months.
RF: The orange line portrays the temperature forecasts made by the RF model. These models forecasts appear more articulated fluctuations, reflecting the models affectability to changes within the data.
Hybrid SVM-RF: The gray line shows the temperature expectations made by the Hybrid SVM-RF model, which combines the strengths of both the SVM and RF models. These models forecasts illustrate an adjusted trend, capturing both stability and changeability within the temperature data.
The chart shows that whereas each show gives different forecasts, the Hybrid SVM-RF model aims to offer a more accurate and stable forecast by leveraging the advantages of both the SVM and RF models. This visualization makes a difference in understanding the comparative execution of the models and their capacity to generalize the temperature trends in Khartoum.

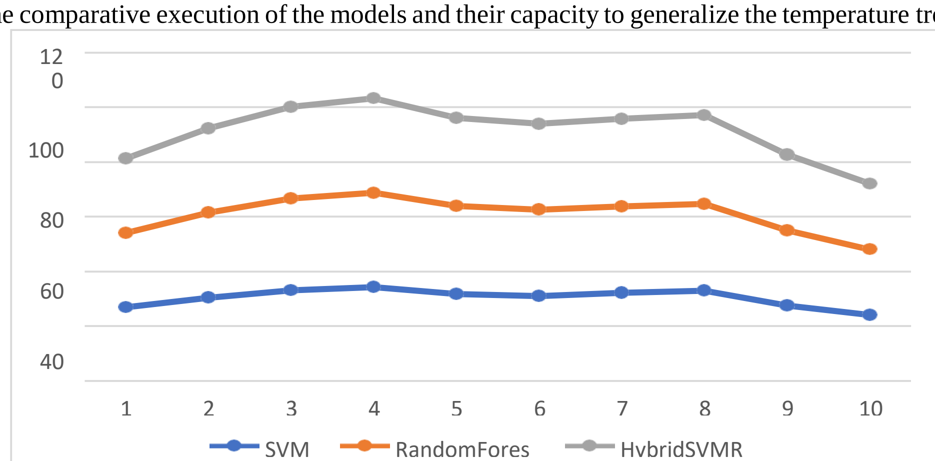

Figure 5. Forecasting Temperature in Khartoum.

5. CANCELATION

In this study, we have effectively created and executed a machine learning-based temperature-forecasting show for Khartoum utilizing CRU data from 1901 to 2022. The broad historical dataset given by CRU was instrumental in training our models to recognize and forecasting temperature patterns with tall accuracy. The application of machine learning and other progressed machine learning strategies allowed us to capture complex transient conditions and move forward forecast unwavering quality.

Conflicts Of Interest

The paper explicitly states that there are no conflicts of interest to disclose.

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