MULTISTATE DEEP SMOOTHED LEARNING ON CASHEW CROP YIELD PREDICTION MODEL EMPHASIZING WIND SPEED AND WIND DIRECTION

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Abstract. This study proposes an enhanced cashew crop yield prediction precision model by incorporating key climatic factors with a major emphasis on wind speed, and wind direction. It employs ensemble deep learning models, including Bi-directional Gated Recurrent Unit (BiGRU) and Multi-Head Attention Mechanism (MHAtt), with data smoothing through the Savitzky Golay method. The ensemble models aim to capture diverse relationships, and global and local dependencies, and enhance generalization and interpretability in model ablation phases. Performance metrics, including MAPE, MAE, RMSE, R^2, and SHAP values, confirm the accuracy of the proposed model, achieving an impressive R^2 score of 0.87. The study explores how each model interprets feature engineering, emphasizing the role of environmental parameters, especially wind speed and wind direction. It also compared the remote data with ground-measured data highlighting that remote sensing data remains reliable and valuable for various applications. This analysis contributes insights for improving cashew yield predictions and highlights the significance of feature engineering in ensemble deep learning models.
Keywords: *cashew, ensemble, multi-head, wind speed, wind direction, crop forecast*

Introduction

The cashew tree (*Anacardium occidentale* L.) is native to Brazil and is a perennial nut-bearing tropical plant that breeds in latitude 15° north and south of the equator. This research considers this crop because it is a multi-use tree crop with great economic value to third-world countries including Benin Republic, Brazil, Cote d'Ivoire, Guinea Bissau, Ghana, India, Mozambique, Nigeria, Philippines, Sri Lanka, Tanzania, Vietnam (Adeigbe

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et al., 2015; Boafo and Lyons, 2021; UNCTAD, 2021; Hashmiu et al., 2022). Cashew crop farming although not intensively regularized in Ghana, provides jobs to thousands of people locally, especially the youth and women. The crop is estimated to be mainly cultivated by 1.5 million small-scale farmers (SNRD, 2019). Meanwhile, this crop has received little research in crop yield prediction using advanced deep-learning models (Balogoun et al., 2015; Das et al., 2022). Most of these researchers focused on conventional features that enable cashew crops to yield wholesomely. This motivated us to research yield prediction using advanced deep-learning models while using unconventional environmental features.

Deep learning (DL) algorithms have undergone rapid evolution over the past three decades, yielding promising approaches that outperform traditional machine learning (Véstias et al., 2019). This evolution presents a unique opportunity to leverage agricultural statistics as training data directly, making deep learning a powerful tool in this domain (Zhong et al., 2019). However, choosing the best approach for time series forecasting among these techniques, often labeled as "black-box models," can be challenging.

Artificial intelligence (AI) technology, mimicking human intelligence in technology, has become integral, gaining significant traction in hydrological forecasting (Ma et al., 2022; Zhou et al., 2022; Sankalp et al., 2023). Cashew producers aiming for higher yields frequently encounter challenges related to climate, farming practices, the quality of expertise, and land topology (Chahal and Gulia, 2020; Feng et al., 2021). The accuracy of DL results relies on several factors (Nti et al., 2022), with a precise dataset being a critical consideration. Noise in data can stem from various sources, including measurement errors, data collection artifacts, and environmental factors. Techniques like Savitzky Golay, Fourier transforms, wavelet transforms, and statistical methods such as averaging or smoothing can be employed to address these challenges (Hastie et al., 2009; Witten et al., 2011).

In this study, we conduct experiments using a multistate deep learning model with a cashew crop dataset. The employed models include the Bi-directional Gated Recurrent Unit (BiGRU) (Ali et al., 2018; Chu et al., 2019; Ye et al., 2024), and the Multi-Head Attention mechanism (MHAtt) (Vaswani et al., 2017). The objective is to identify the underlying effects of environmental parameters, especially wind speed and wind direction on cashew crops using these advanced multistate models. To enhance the dataset for improved model performance, we apply the Savitzky Golay filter as an initial preprocessing step. The primary aim of this filtering is to eliminate unwanted or random variations and errors that may be present in the data (Witten et al., 2011). Recognizing the type and sources of noise in a dataset is crucial for proper data preprocessing and analysis to reduce edge effects using polynomial fitting and approximation while boosting the computational efficiency of the ensembled model. The data is then smoothened and fed into various ensemble deep-learning models to uncover the intricate relationships between environmental parameters and cashew crop outcomes.

Data accuracy and quality hinge on the reduction of noise, making it challenging to discern meaningful patterns or relationships (Witten et al., 2011). Employing data smoothing techniques, such as fitting a low-degree polynomial using Savitzky Golay to successive sets of data points, enables the removal of noise while preserving essential features although (Schmid et al., 2022) the Savitzky Golay is proposed to be replaced due to poor noise suppression. As noted by He et al. (2022); Song et al. (2022) and Sankalp et al. (2023), the Bi-directional Gated Recurrent Unit (BiGRU) emerges as a variant of

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the GRU architecture. This integration allows for the bi-directional processing of sequential data, involving two parallel GRU layers running concurrently. This enhancement further augments the ability of the model to capture contextual information from both past and future sequences.

Multi-head attention mechanism involves performing attention calculations multiple times in parallel, with each instance having its own set of learnable parameters (Kaur et al., 2023) Hence, the optimization of the model performance aimed to attain a satisfactory result. The integration of smoothed analysis, advanced RNN models, and a multi-head attention mechanism was strategically designed to leverage the effectiveness of these models. The objective was to underscore the impact of environmental parameters, including wind speed, wind direction, drought (Bediako-Kyeremeh et al., 2024), and soil moisture, on predicting cashew yield in Ghana.

On the other hand, a Multi-Head Attention mechanism is an extension of self-attention where multiple sets of attention weights are computed in parallel (Vaswani et al., 2017). Each "head" learns different relationships and provides a different perspective on the data. The results from multiple heads are then concatenated or linearly combined to produce the final output (Vaswani et al., 2017).

The accuracy of a model primarily relies on data precision, effective management of potential outliers, and normalizing the dataset to facilitate a well-fitted model for optimal learning. The rationale for this experiment can be summarized in three key aspects:

- Improving data quality with Savitzky Golay Filter for smoothed data and mitigate edge effects although research proposes it be replaced due to its ineffectiveness.
- Transferring the smoothed data into a multistate ensemble model for crop yield prediction in ablation
- Understanding the environmental impact analyzed using a feature model, considering the impact of wind speed and wind direction in enhancing crop yield.

Materials and Methods

Data

A multi-sourced dataset was employed, including data from the Ghana Meteorological Agency (GMet), which covered environmental parameters like meteorological drought resulting from extended periods of below-average precipitation. This led to a moisture deficiency, particularly affecting the chosen crop for this research, which thrives in semi-arid regions. This dataset spans the period from 1999 to 2018, covering a 20-year timeframe and focusing on the three cashew-growing municipalities.

Additionally, datasets related to cashew yield production were obtained from the Ministry of Food and Agriculture (MoFA)for the municipalities under study. The data collection aligned with the specified study period, and the targeted cashew growing areas included Jaman North, Jaman South, and Wenchi, spanning from 1999 to 2018.

Remote sensing data for the three study areas was acquired from the Prediction of Worldwide Energy Resource | Data Access Viewer enhanced (POWER | DAVe, 2023). POWER | DAVe, a tool from NASA's POWER (Prediction of Worldwide Energy Resources) project, is a Data Access Viewer offering solar radiation and meteorological datasets from NASA research. These datasets are useful for applications like renewable energy, building energy efficiency, and agriculture (Rodrigues and Braga, 2021). The tool enables users to visualize, analyze, and download relevant climate data for their needs. These datasets were accessed in 2023. The dataset includes crucial weather parameters

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such as soil moisture, wind speed at 2 m, and wind direction at 10m, spanning the study period from 1999 to 2018. These additional parameters are essential for assessing and promoting sustainable crop yield, including applications like eco-friendly or sustainable farming (van Delden et al., 2021).

The environmental parameter selection criteria were based on several research focusing on conventional environmental parameters such as temperature, precipitation, evapotranspiration, humidity, and drought among others. Whereas little is research on wind speed and wind direction, we term these two parameters as unconventional environmental parameters. This is because cashew crops require effective crop pruning for airflow involves the deliberate removal of certain parts of a crop, such as branches or foliage, to improve airflow within the crop canopy. This practice is commonly employed in agriculture, especially in densely planted crops, to enhance ventilation, reduce humidity levels, prevent the development of diseases caused by poor air circulation, and increase yield (Bediako-Kyeremeh et al., 2024).

Drought and soil moisture are crucial factors for growing cashew trees in semi-arid regions (Osibo et al., 2024). While cashew trees are relatively drought-tolerant, prolonged drought can stress the trees, reducing growth and yield, particularly during critical periods like flowering and fruiting. Drought can also encourage deeper root systems, which helps in accessing groundwater, but excessive drought can damage roots and reduce nutrient uptake (Sankalp et al., 2023). Consistent soil moisture is essential for nutrient absorption, overall tree growth, and productivity, especially for young trees. Proper soil moisture levels also improve nut size, weight, and overall yield (Balogoun et al., 2015; Bediako-Kyeremeh et al., 2024). *Fig. 1* demonstrates the effectuality of wind speed and wind direction as a plausible environmental parameter for cashew yield.

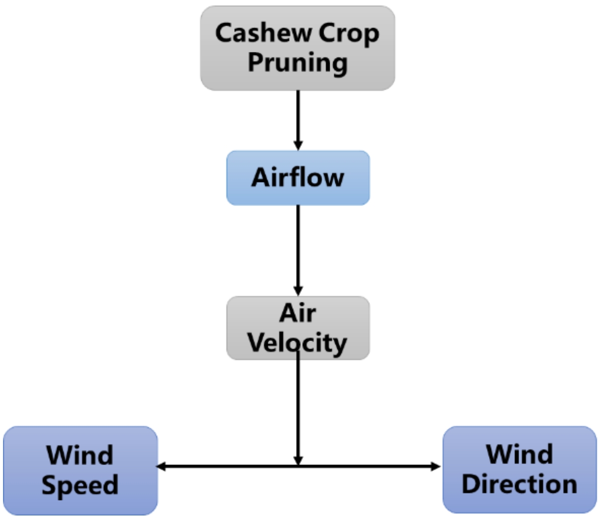

Figure 1. *Demonstrate the flowchart of the importance of wind speed and wind direction for sustainable cashew farming*

Study Area

The study area encompasses coordinates 7°51'0" N and 2°31'60" W, situated in the Bono region of Ghana. Specifically, three districts Jaman North, Jaman South, and Wenchi were chosen for this research. These municipalities are renowned for their cashew production. *Fig. 2* provides a visual representation of the study area.

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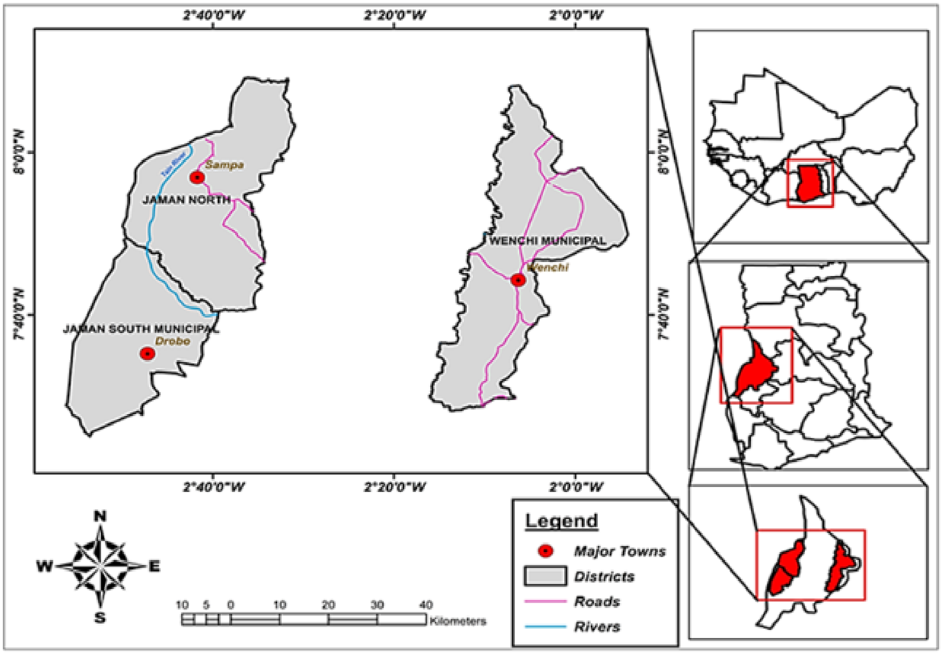

Figure 2. *Study area showing the three cashew-growing municipalities in the Bono Region (Jaman North, Jaman South, and Wenchi), within Ghana and the West African continent*

Data Preprocessing

Savitzky Golay Smoothing

The Savitzky-Golay filter for data preprocessing involves smoothing noisy data to reduce noise while preserving important features in the signal (Savitzky and Golay, 1964; Schmid et al., 2022). We intend to showcase the flexibility of the Savitzky-Golay filter in adjusting parameters like polynomial degree and window size. Additionally, Savitzky-Golay highlights the filter's ability to mitigate edge effects through polynomial approximations, emphasizing its practical relevance in real-world data analysis. The results of the Savitzky Golay preprocessing from the original noise to the smoothed data are plotted.

This function will return the smoothed data. The expression for Savitzky Golay is defined below in *Eq.1*:

$$y_{smoothed}\left[n\right]=\sum_{i=k}^{k}c_i.y\left[n+i\right] \qquad \text{(Eq.1)}$$

where:

y_n is the smoothed value at position n

k represents the input signal values at positions $n + i$

c_j are coefficients of the polynomial.

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Deep Learning Models

Bi-directional Gated Recurrent Unit

BiGRU extends the basic GRU (Gated Recurrent Unit) by processing the input sequence in both forward and backward directions. In this work, we apply the current forward and backward hidden states which are calculated to represent the network's memory or internal representation of the input sequence and combined utilizing concatenation to produce the present hidden, this will enable the model to leverage information from both directions, providing a more comprehensive understanding of the input sequence. The adaptation of this model is to better understand the relationships and dependencies within the input data from the Savitzky-Golay filter output, leading to improved performance in prediction tasks. The mathematical expressions for the forward and backward GRU units in a BiGRU entire process as implemented by Qiao et al. (2023) can be defined as follows in *Eq.2*:

$$\begin{aligned} \vec{h}_t &= GRU\left(x_t, \vec{h}_{t-1}\right) \\ \overleftarrow{h}_t &= GRU\left(x_t, \overleftarrow{h}_{t-1}\right) \\ h_t &= w_{\vec{h}_t}\vec{h}_t + w_{\overleftarrow{h}_t}\overleftarrow{h}_t + b_t \end{aligned} \tag{Eq.2}$$

where:

$\vec{h}_t$ represent the hidden state of the forward GRU at time step *t*.

$\overleftarrow{h}_t$ represent the hidden state of the backward GRU at time step *t*.

x_t represent the input at time step *t*.

Multi-Head Attention Mechanism

The capability of our model to jointly attend to information from another dimension, a multi-head attention mechanism is integrated into our model to learn patterns from targeted features (Vaswani et al., 2017), after modeling our data, concatenating results from the model, and evaluating results. The introduction of the multi-head attention allows the model to focus on different parts of the input sequence simultaneously, with each attention head attending to different aspects of the input, enabling the model to capture a diverse set of features and relationships within the data for expressive and robust representations. This is expected to improve learning and reduce attention redundancy by allowing heads to redundantly attend to the same information from different perspectives while capturing dependencies at different time scales. The multi-head attention mechanism can be mathematically expressed as follows in *Eq.3*:

Linear Transformation of Q, K, and V: For each head "*i*" (where *i* ranges from 1 to the number of attention heads "*h*"):

$$Attenttion(Q_i, K_i, V_i) = soft\max\left(\frac{Q_i K_i^T}{\sqrt{d_k}}\right)V_i \tag{Eq.3}$$

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where:
W_{Q*i*}, W_{K*i*}, and W_{V*i*} are learnable weight matrices specific to each attention head.}}

Given an input sequence of queries (Q), keys (K), and values (V), where each of these is a matrix:

Q: Query matrix of shape (*batch_size, seq_length_q, d_model*)

K: Key matrix of shape (*batch_size, seq_length_k, d_model*)

V: Value matrix of shape (*batch_size*, *seq_length_v, d_model*)

where:
batch_size: The number of examples in a batch.
seq_length_q: The length of the query sequence.
seq_length_k: The length of the key sequence (which might differ from *seq_length_q*).
seq_length_v: The length of the value sequence (which might differ from *seq_length_q*).
d_model: The dimensionality of the input embeddings.

Model Construction

Our model construction involved several key components, starting with Savitzky-Golay preprocessing, followed by the incorporation of BiGRU (Bidirectional Gated Recurrent Unit), and a Multi-Head Attention Mechanism. For data preprocessing using the Savitzky Golay filter, aiming to smooth and reduce noise in our cashew and environmental parameter time series data. We determined the Savitzky-Golay filter parameters with window size (5) since larger windows preserve more features but may smooth less, while smaller windows provide stronger smoothing. The polynomial degree and Derivative order were set to (2) respectively. This degree affects the smoothness of the fitted curve. The savgol_filter function was used to apply the Savitzky-Golay filter to our cashew noisy data. The time series input with a shape of (timesteps, and features). The Conv1D layer with linear activation serves as a Savitzky-Golay filter.

The introduction of BiGRU allowed the model to capture information from both past and future sequences, utilizing 32 units. A tanh and sigmoid activation function and recurrent activation respectively. The BiGRU layer had a bias input shape of (420, 5), a dropout rate of (0.2), and a concatenating merge mode. The Multi-Head Attention Mechanism layer was then employed to enable the model to focus on different segments of the input sequence simultaneously. This enhanced the model's ability to capture complex patterns, transitioning from the BiGRU layer to generate a final regression output. We applied (5) heads, Key, Value and Query Dimensions (*sequence_length = 420*), (*feature_dim =128*), (*num_heads = 5*), (*head_dim = 32*). We maintained the attention dropout rate at (0.2). The model was compiled and trained using the Adam optimizer algorithm and Mean Squared Error (MSE) as the loss function.

For the training process, we utilized a test-train split of the dataset with a random state of (42), a test size of (0.2), and (5) epochs. After training, we employed SHAP values for model interpretability, providing insights into the influence of each feature on the model's predictions. Additionally, traditional evaluation metrics such as MAPE, MAE, MSE, R^2, and RMSE were employed to assess the overall performance of our predictive ensemble model. *Fig. 3* illustrates the proposed ensembled model composition.

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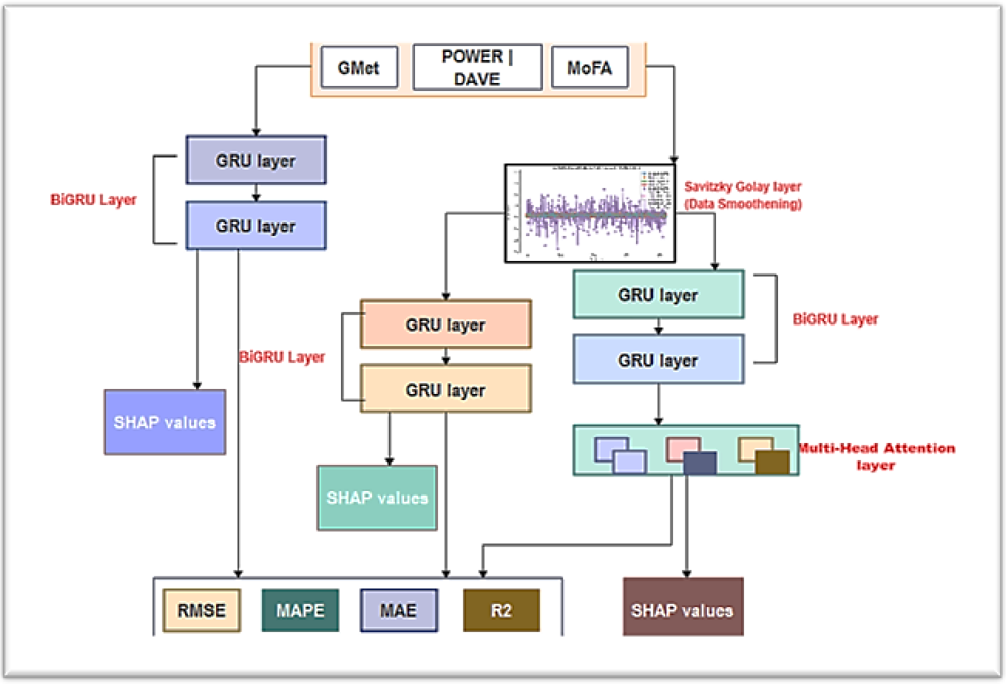

Figure 3. *Savitzky Golay- BiGRU-Multi-Head Attention Mechanism model architecture*

Evaluation Metrics

Model performance was analyzed using regression metric tasks such as:

Root Mean Square Error (RMSE). RMSE applied to achieved results can be expressed in *Eq.4* as:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}} \qquad \text{(Eq.4)}$$

where:
n is the of observations
Pi is the simulated (predicted) value for the *i-th* observation.
Oi is the observed value for the *i-th* observation.

Coefficient Determinant (R^2): The R^2 can be expressed below in Eq.5:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_1 - \hat{y}_1)^2}{\sum_{i=1}^{n} (y_1 - \bar{y}_1)^2} \qquad \text{(Eq.5)}$$

where:
n is the number of observations
Yi is the observed value for the *i-th* observation
$\hat{y}_i$ is the predicted value for the *i-th* observation
$\bar{y}_i$ is the mean of the observed values.

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Mean Absolute Error (MAE): MAE was instrumental in achieving our results and be expressed in *Eq.6* below:

$$MAE = \frac{\sum_{i=1}^{n} | y_i - x_i |}{n} \quad \text{(Eq.6)}$$

where:
|*yi-xi*| = absolute errors and Σ = summation symbol

Mean Absolute Percentage Error (MAPE): Interpreting our results using MAPE can be expressed mathematically below in *Eq.7*:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{P_i - O_i}{P_i} \times 100 \quad \text{(Eq.7)}$$

Results

In this section, we discuss the results accomplished from this research. These results comparatively show how with and without ensembled deep learning models combined with multi-head attention mechanisms and a Savitzky Golay smoothed analysis yield positive on cashew yield production dataset and climatic factors. *Fig. 4* visually displays the results of selected dataset features before and after Savitzky Golay smoothed data analysis. The analysis involved the application of smoothed data using the Savitzky Golay filter on selected features, including soil moisture drought, wind speed, and wind direction. This process aimed to diminish data noise while retaining crucial features. It achieved this by fitting a low-degree polynomial within a given range and utilizing the polynomial coefficients to forecast the smoothed value at essential points.

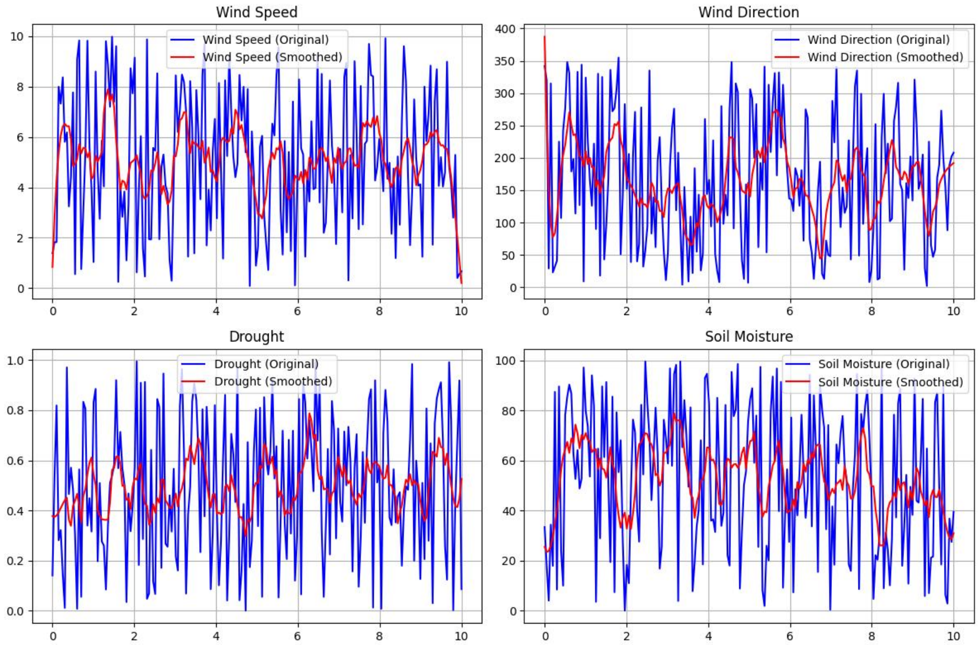

Figure 4. *Savitzky Golay smoothed data analysis of selected features of the dataset*

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Fig. 4 visualizes four plots showing both the original (blue) and smoothed (red) data for wind speed, wind direction, drought, and soil moisture over a 10-unit period. The wind speed plot exhibits high variability in the original data, with the smoothed line revealing general trends more clearly. The wind direction plot shows similar behavior, with significant fluctuations in the original data and clearer patterns in the smoothed line. The drought data is erratic, but the smoothed line highlights underlying trends. Lastly, the soil moisture plot displays high variability in the original data, with the smoothed data providing a clearer trend. The significance of the Savitzky Golay smoothed data aside from noise reduction provides an avenue of parameter tuning and reduces edge effects with its polynomial approximations and computational efficiency. The data points for the selected features are strategically positioned around the central point. The results demonstrate a balance between the smoothed and captured local variations. This is considered effective when dealing with signs that demonstrate both smooth trends and rapid variation. This methodology aligns with the approach employed by Cao et al. (2018) who utilized the Savitzky Golay filter to enhance the quality of NDVI time-series data by incorporating spatiotemporal information.

The primary objective of this research was to predict cashew yield, employing various ensemble deep learning models such as BiGRU, Savitzky Golay-BiGRU, and Savitzky Golay-BiGRU-Attention Mechanism with emphasis on wind speed and wind direction. The focus was on determining the most effective ensemble deep learning model with and without smoothed data. *Table 1* provides an ablation of a comprehensive overview of the experimental results, utilizing evaluation metrics such as MAPE, MAE, RMSE, and R^2 to comprehensively showcase the model performance.

Table 1. *Comparison of overall model performance using evaluation metrics with other predictive models (Ablation)*

Individual Deep Learning Model	**Performance Evaluation Matrics**			
	MAE	**R^2**	**RMSE**	**MAPE**
BiGRU	1.86	0.6810	0.772	8.121%
Ensembled Model				
Savitzky Golay-GRU-BiGRU	1.52	0.826	0.8301	5.62%
Savitzky Golay-BiGRU-Multi-Head Attention Mechanism **(Our Model)**	0.1766	0.8705	0.9822	3.91%

In contrast, our model, incorporating Savitzky Golay, BiGRU, and a multi-head attention mechanism, demonstrated superior performance compared to the ensemble model featuring Savitzky Golay, and BiGRU only. This improvement can be attributed to the inclusion of Savitzky Golay and the attention mechanism, which enables the model to selectively focus on different segments of the input sequence with varying levels of attention to smoothed data (Vaswani et al., 2017).

Several studies, including those by He et al. (2022); Kaur et al. (2023); and Sankalp et al. (2023), have employed BiGRU, and attention mechanisms in predicting vegetation and yield. However, these authors did not consider the influence of wind speed and wind direction, in addition to drought and soil moisture. These environmental parameters have been the focus of numerous research endeavors aimed at determining their effectiveness in the prediction of agricultural outcomes.

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Savitzky and Golay (1964) advocate for the adoption of a simplified least squares procedure to preprocess datasets, effectively smoothing and distinguishing noise from genuine data. This process ensures that the data is in an optimal state for subsequent modeling. The effectiveness of this approach is supported by compelling results, as reflected in evaluation metrics such as the Mean Absolute Percentage Error (MAPE), indicating the accuracy of the predictive model. About *Table 1*, where a MAPE of 3.91% was achieved, this value is indicative of a highly accurate model. Our model's predictions closely align with the actual values, as evidenced by the low MAE (0.1766), high R^2 (0.87), and low RMSE (0.9822) scores, affirming the model's precision in predicting outcomes. Notably, when compared to two other contemporaneous models that were independently experimented with the same computational requirements and dataset, our Savitzky Golay-BiGRU-Attention Mechanism model outperformed them. *Fig. 5* visually represents the performance of the Savitzky Golay-BiGRU-Attention Mechanism model, specifically highlighting the Multi-Head Attention Mechanism. The regression chart in *Fig. 5* demonstrates the proximity of data points on both sides of the regression line, illustrating a close correspondence between predicted and actual values.

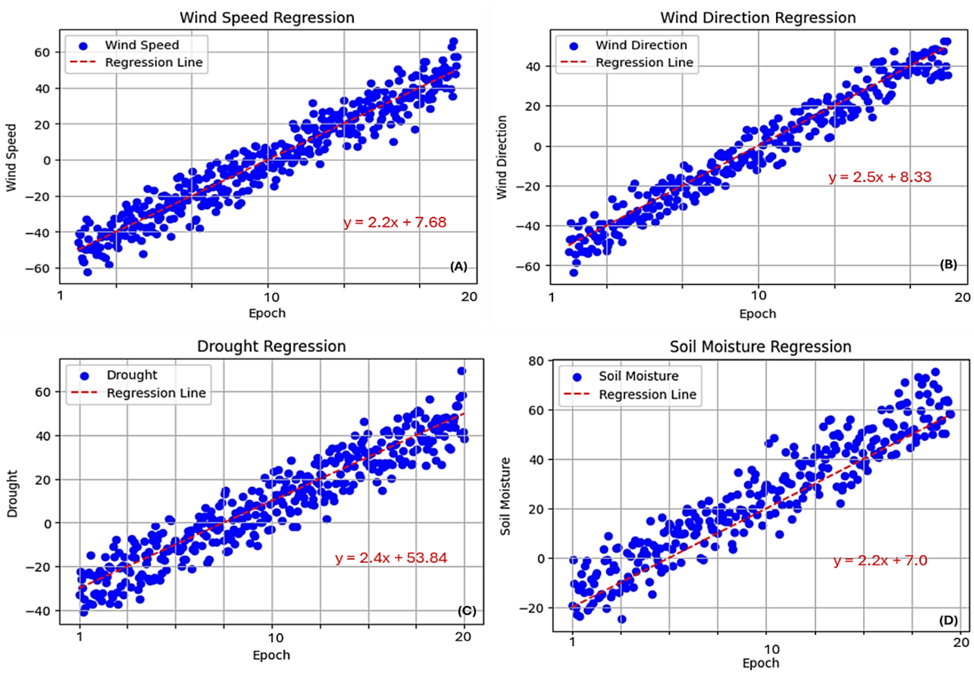

Figure 5. *Regression line chart of overall model (Savitzky Golay-BiGRU-Multi-Head Attention Mechanism) performance*

Fig. 5 visualizes four regression plots depicting the relationships between epochs and various environmental parameters: wind speed, wind direction, drought, and soil moisture. Each plot includes a regression line, indicating positive linear trends for all parameters: (y = 2.2x + 7.68) for wind speed, (y = 2.5x + 8.33) for wind direction, (y = 2.4x + 53.84) for drought, and (y = 2.2x + 7.0) for soil moisture. These positive linear relationships suggest that these environmental factors increase over time, which is crucial for improving the accuracy of predictive models.

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Detailed results are documented in *Table 2*, where individual municipalities like Jaman North, Jaman South, and Wenchi underwent assessment using evaluation metrics such as R^2 to provide a comprehensive overview of the model's performance.

Table 2. *Individual municipalities' performance of dependent and independent variables*

Municipalities	**Performance Evaluation (R^2)**
Jaman North	0.8
Jaman South	0.91
Wenchi	0.882

Validating remote data with ground-measured data is essential for ensuring the accuracy, reliability, and utility of remote sensing technologies. This validation process builds confidence in the data and models derived from remote sensing, ultimately enhancing their application across diverse fields. *Fig. 6* visualizes the validation of remote data and ground-measured data correlation.

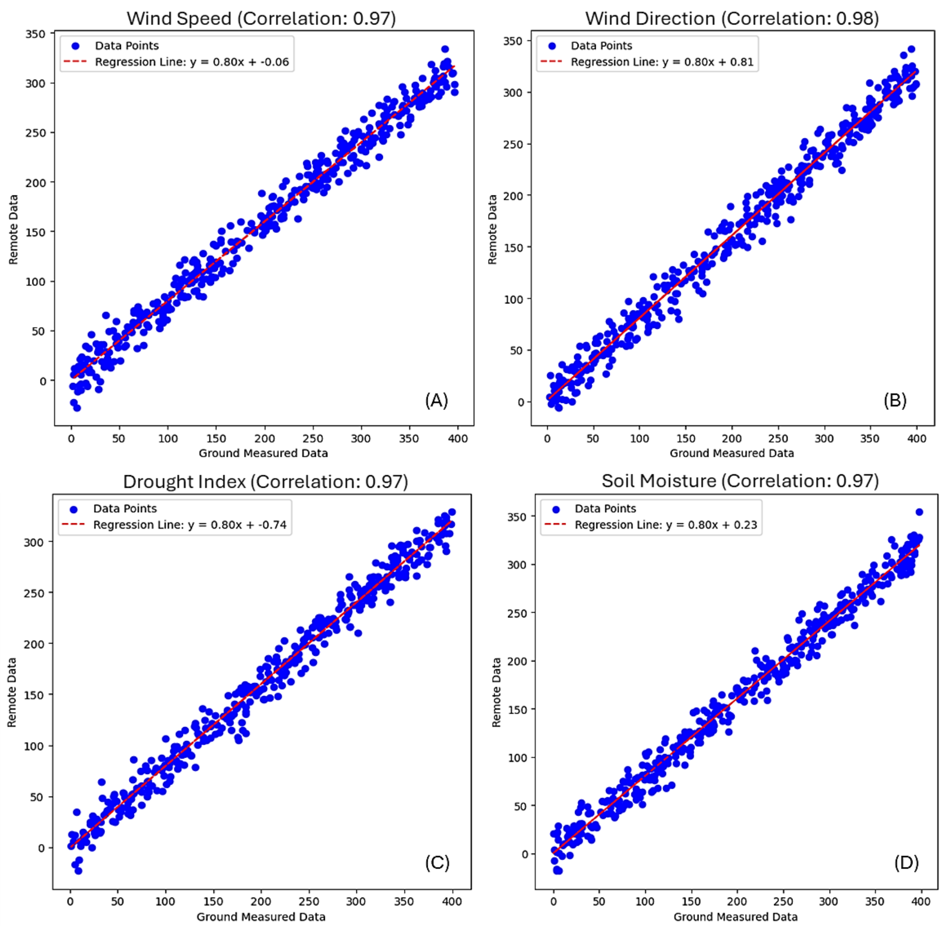

Figure 6. *The line chart displays the correlated remote and ground-measured data for the four variables (wind direction, wind speed, drought index, and soil moisture) over 20 years*

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Fig. 6 presents four graphs showing the correlation of remote data and ground-measured data over the period from 1999-2018 for selected environmental parameters such as wind direction, wind speed, drought index, and soil moisture. Each plot includes a regression line with its equation and a legend to illustrate the correlation visually.

Discussion

The study's innovative use of ensemble deep learning models, including Bi-directional Gated Recurrent Unit (BiGRU) and Multi-Head Attention Mechanism (MHAtt), effectively captures these trends, enhancing the precision of cashew crop yield predictions. The integration of data smoothing techniques like the Savitzky Golay method further contributes to the model's robustness and reliability. This approach validates the inclusion of specific climatic factors and highlights the potential of advanced deep-learning models to interpret complex environmental data, providing valuable insights for agricultural forecasting and decision-making. The evaluation metrics, MAPE and MAE, were chosen with specific objectives. R^2 aims to provide an interpretable scale in the same units as the target variable, indicating the proportion of variance explained by the model. On the other hand, MSE puts more emphasis on large errors than MAE. It is worth highlighting from *Table 1* that our newly suggested model achieved superior prediction accuracy compared to our other predictive models. The incorporation of the Savitzky-Golay filter aimed at refining the data and enhancing its features resulted in an improved performance. Notably, the noise suppression was not prominently evident, but the obtained results proved to be beneficial, as reported (Schmid et al., 2022), We highly recommend the utilization of the Savitzky-Golay filter, as it possesses the capability to enhance data, yielding meaningful and significant results. In *Table 2*, the model performance for Jaman South exhibited an R^2 score of 0.91, suggesting that approximately 91% of the variance in the dependent variable is explained by the model, this is generally considered a strong fit. For Wenchi, the R^2 score of 0.882 indicates that 88.2% of the variance in the dependent variable is explained, demonstrating a good fit, albeit slightly lower than Jaman South. Lastly, Jaman North achieved an R^2 score of 0.8, explaining approximately 80% of the variance in the dependent variable. It's important to note that R^2 values closer to (1) signify a better fit of the model to the data. The total R^2 score represents the average goodness of fit across the three municipalities. *Figs. 7, 8*, and *9* visualize the feature trends and patterns from *Table 2* in a column chart. The selected environmental features such as wind direction, wind speed, drought, and soil moisture are highlighted as factors influencing cashew crop yield in individual municipalities.

In *Fig. 6* Wind Speed (a) showed a regression line equation is y=0.80x+0.06y indicating a strong positive correlation between remote and ground-measured data points. Wind Direction (b) also shows a strong positive correlation with a regression line equation of y=0.80x+0.81, Drought Index with y=0.80x+0.74, signifying a robust positive correlation and Soil Moisture (d) explained with a regression line y=0.80x+0.23, reflecting a strong positive correlation as well. These selected environmental feature plots demonstrate that remote data is consistently aligned with ground-measured data, validating the reliability of remote sensing for monitoring and predicting environmental parameters over the two-decade period.

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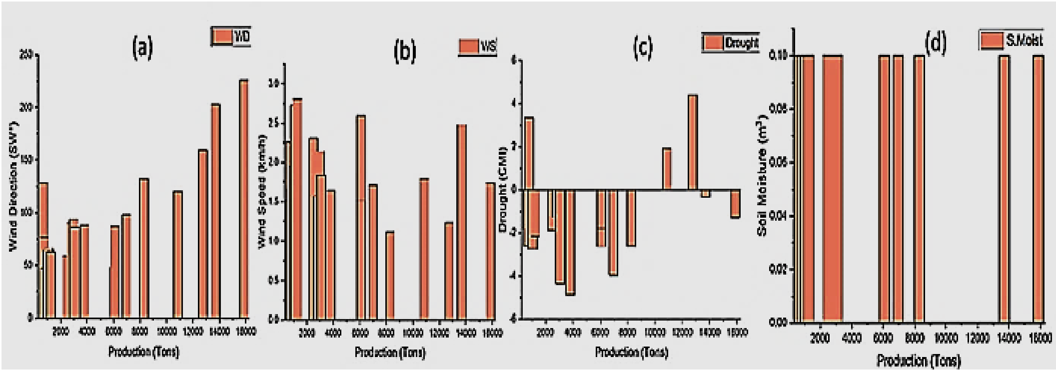

Figure 7. *(a)-(d). Column chart showing feature trends and patterns of Jaman North Municipality*

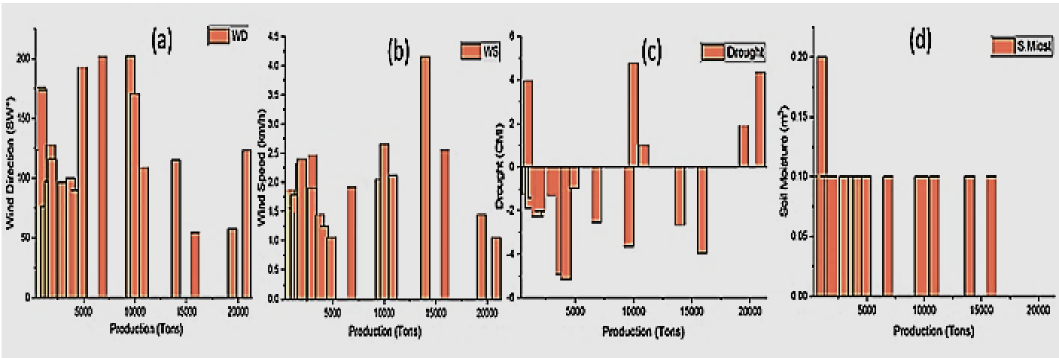

Figure 8. *(a)-(d). Column chart visualizing feature trends and patterns of Jaman South Municipality*

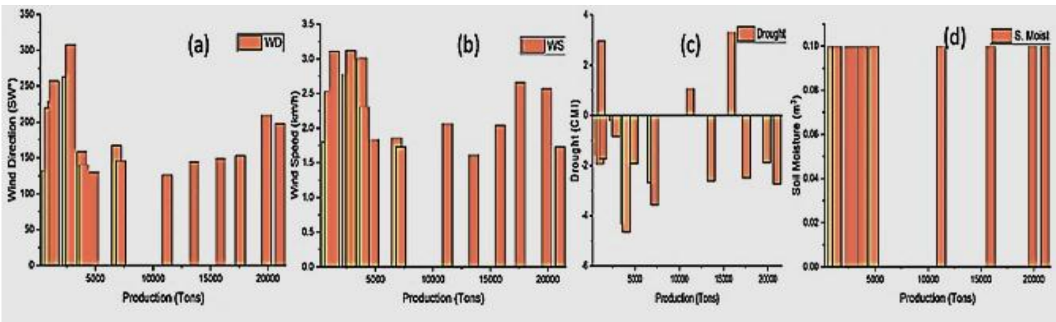

Figure 9. *(a)-(d). Column chart visualizing feature trends and patterns of Wenchi Municipality*

The consistency in data points around the regression lines underscores the accuracy of remote sensing, essential for applications in weather forecasting, agricultural planning, water resource management, and disaster preparedness. Validation with ground-measured data ensures the credibility of remote sensing, helping to detect and correct any biases, thus enhancing the reliability of these data for practical use (Gella et al., 2021). While exact matching is not required, the consistent trends observed validate the applicability of remote data in various fields, contributing to more informed decision-making and efficient resource management (Arshad et al., 2023). These differences can

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lead to variations in data, as remote sensors might average values over larger scales, whereas ground measurements offer point-specific precision. Additionally, the need for regular calibration and validation of remote sensors against ground-truth data can contribute to discrepancies if calibration is insufficient or ground-truth data are sparse (Birungi et al., 2024; Tian et al., 2021). Despite these challenges, the discrepancies can positively impact research by driving the refinement of remote sensing models and enhancing data integration. Combining the strengths of both remote and ground data leads to a more comprehensive understanding of environmental conditions, improved validation frameworks, and broader applications across fields such as agriculture, forestry, and climate science. This iterative process ensures that remote sensing data remains reliable and valuable for various applications (Osibo, Ma, Bediako-Kyeremeh, et al., 2024; Zhong et al., 2019).

In the context of cashew yield, it is crucial to identify multiple factors that influence the outcome. Numerous environmental parameters, including evapotranspiration, temperature, precipitation, radiation, and NDVI (Normalized Difference Vegetation Index), among others, are commonly examined by researchers. These factors play significant roles in understanding and predicting cashew crop yields as claimed by Basso and Liu (2019); Khaki and Wang (2019); Nigam et al. (2019); Khaki et al. (2020); Keerthana et al. (2021); and Bhimavarapu et al. (2023). The primary focus of this research was to concentrate on four specifically chosen features that have both direct and indirect impacts on the yield of cashew crops in semi-arid regions. The aim was to highlight the positive effects that these selected features contribute to cashew yield in Ghana.

To establish this concept, *Figs. 7(a,b), 8(a,b),* and *9(a,b)* were utilized to compare the effects of wind direction and wind speed over the study periods for each of the three individual studies. The results indicated that our Savitzky Golay-BiGRU-Multi-Head Attention Mechanism model exhibited significant occurrences of wind direction and wind speed during periods of pronounced production. This reinforces the notion that both wind speed, measured in kilometers per hour (km/h), and wind direction, observed using cardinal degrees (°) of southwest winds, suggest wind conditions that are considered not too strong (Tempest, 2023). Hence, the cashew crops experienced favorable winds conducive to progressive yields over the specified periods. This observation aligns with findings from previous research (Kalantari et al., 2018; Beacham et al., 2019; van Delden et al., 2021) this underscores the importance of embracing sustainable farming practices that incorporate environmental parameters throughout the cultivation, harvesting, and post-harvest periods of cashew crops. *Figs. 7, 8,* and *9* elucidate various trends observed in the results of the study area, particularly about selected environmental features. The analysis of these environmental feature trends was juxtaposed against production data from the respective study areas. Notably, when examining the correlation between wind direction and production, Jaman South demonstrated a positive trend in production as opposed to Jaman North and Wenchi.

There is existing research that delves into the impact of wind speed on crop yield, emphasizing the significance of considering such environmental factors in agricultural practices. Balogoun et al. (2015) considered the influence of wind speed on crop yield along with other environmental parameters, there has been a notable gap in considering the direction of the wind, which is intricately linked to the speed of the wind. This emphasizes the need for comprehensive analyses that encompass both wind speed and wind direction for a more thorough understanding of their combined effects on agricultural outcomes. In the work (Das et al., 2022) findings concluded that the

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combined model, formed through an ensemble of deep learning techniques, did not surpass the performance of an individual model in predicting cashew yield. Nevertheless, this study utilized an ensemble deep learning model employing a bagging strategy, coupled with dataset preprocessing, and smoothing using Savitzky Golay. This meticulous process aimed to mitigate noise and enhance the overall quality of the data, thereby contributing to improved results from the ensemble model.

That notwithstanding, it has been researched that cashew yield is excellent in certain soil properties (Adeigbe et al., 2015; Balogoun et al., 2015; Okeke and Akarue, 2018; Boafo and Lyons, 2019; Das et al., 2022) soil drought and soil moisture are peculiar properties of cashew crops due to a soil texture of semi-aridness. *Figs. 7(c, d), 8(c, d),* and *9(c, d)* our ensembled deep learning model visualizes the soil drought and soil moisture which forms a necessary soil texture for cashew crops over the three study areas with cashew production over twenty years. It was evident that in all three study areas, our ensembled deep learning model demonstrated the soil drought was in good soil texture necessary for cashew crop growth while the amount of water needed for the cashew crop to yield was in good proportion as made evident by our Savitzky Golay-BiGRU-Multi-Head Attention Mechanism model. Although, at one point the model depicted no record for certain features at a period these occurrences were slightly insignificant compared to the significance recorded by the model. In general, the trends observed in *Figs. 7, 8,* and *9* indicate that an upswing in both wind speed and wind direction, falling within an optimal wind velocity range, correlates with an augmented yield. Additionally, a moderate rise in moisture levels exhibits a noteworthy increase in yield (Mamelona et al., 2024; Osibo, Ma, Bediako-Kyeremeh, et al., 2024). Moreover, yield experiences growth when soil drought decreases below zero. Instances where zero features were recorded, resulted in zero production, underscoring the significance of these selected environmental variables in cashew nut production.

Moreso, we opted to conduct a detailed analysis of our ensemble deep learning model's performance using SHAP (SHapley Additive exPlanations) values. SHAP values are widely recognized and powerful tools in the realm of explainable artificial intelligence (XAI), offering a cohesive measure of feature importance. Illustrated in *Fig. 10(a)-(c), 11(a)-(c),* and *12(a)-(c)* the SHAP values chart assigns a specific value to each feature for a given prediction, highlighting the contribution of that feature to the model's output. Special emphasis is placed on selected environmental features and their impact on cashew crop production across the three study areas. Throughout the three study areas, the SHAP values chart demonstrates the impact of each specific feature on the model's output, with a focus on their respective mean averages and importance on model output. *Figs. 10, 11,* and *12* strike a balance between local interpretability, elucidating individual predictions, and global interpretability, providing a comprehensive understanding of the overall model behavior. The insights gleaned from SHAP values contribute to the interpretation of our model predictions. The prevailing factors influencing high cashew yields in Jaman South are identified as wind speed and wind direction, distinguishing it from Jaman North and Wenchi. This suggests that the soil moisture level is conducive for optimal cashew production. Analyzing the current data trends and the SHAP feature importance of Wenchi, it is evident that Wenchi is currently leading in production due to soil moisture. Nevertheless, the data indicates a promising outlook for Jaman South to surpass in the coming years, as illustrated by the SHAP values in *Fig. 11(a)-(c).*

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The novelty of this research lies in its comprehensive approach to enhancing cashew crop yield prediction by integrating key climatic factors, particularly wind speed and wind direction, which are often neglected in traditional models.

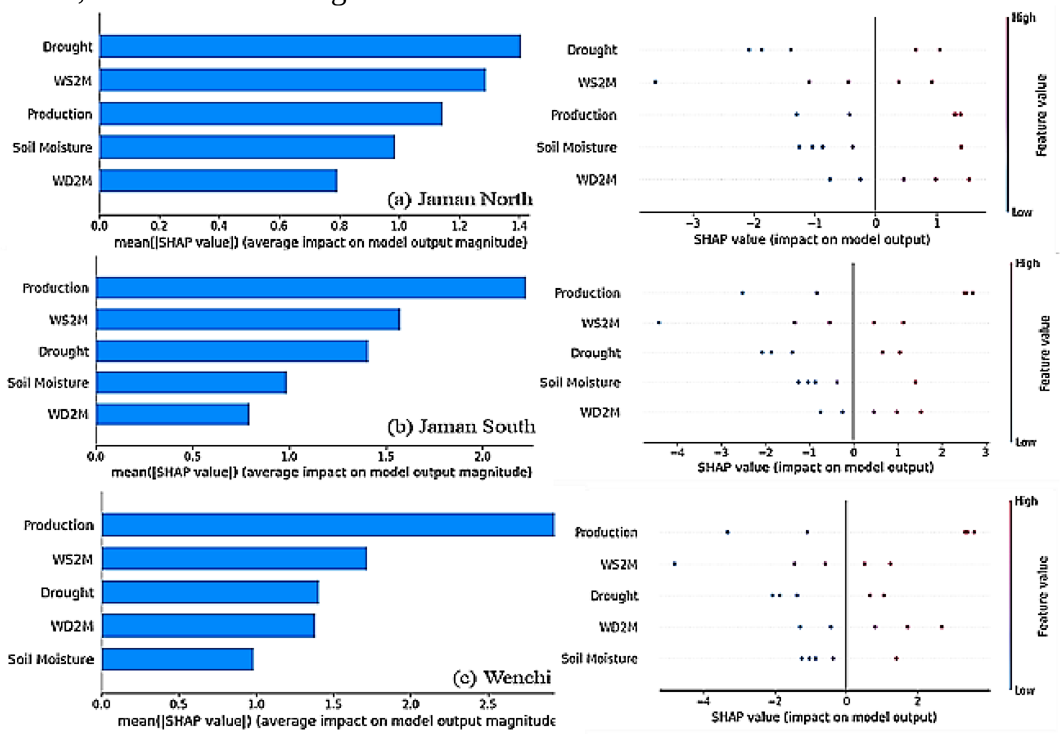

Figure 10. *(a)-(c). SHAP values chart for impact on model output for selected features for the three study areas with individual BiGRU Models*

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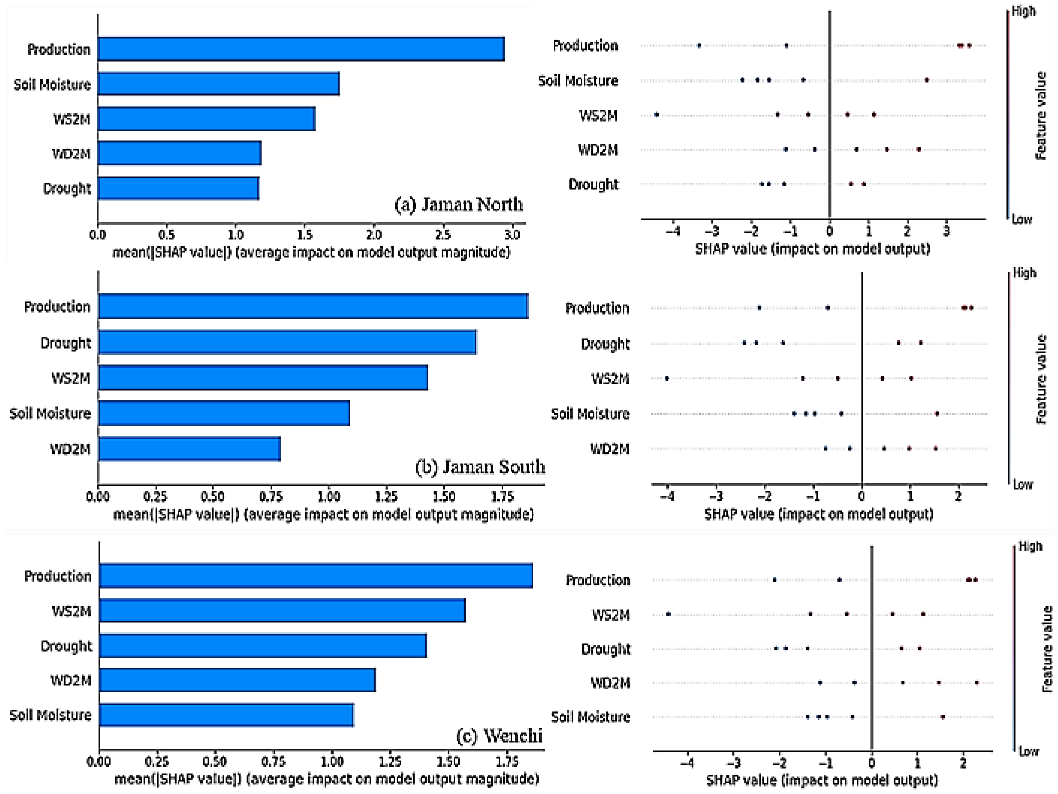

Figure 11. *(a)-(c) SHAP values chart for impact on model output for selected features for the three study areas with individual Savitzky Golay-BiGRU Model*

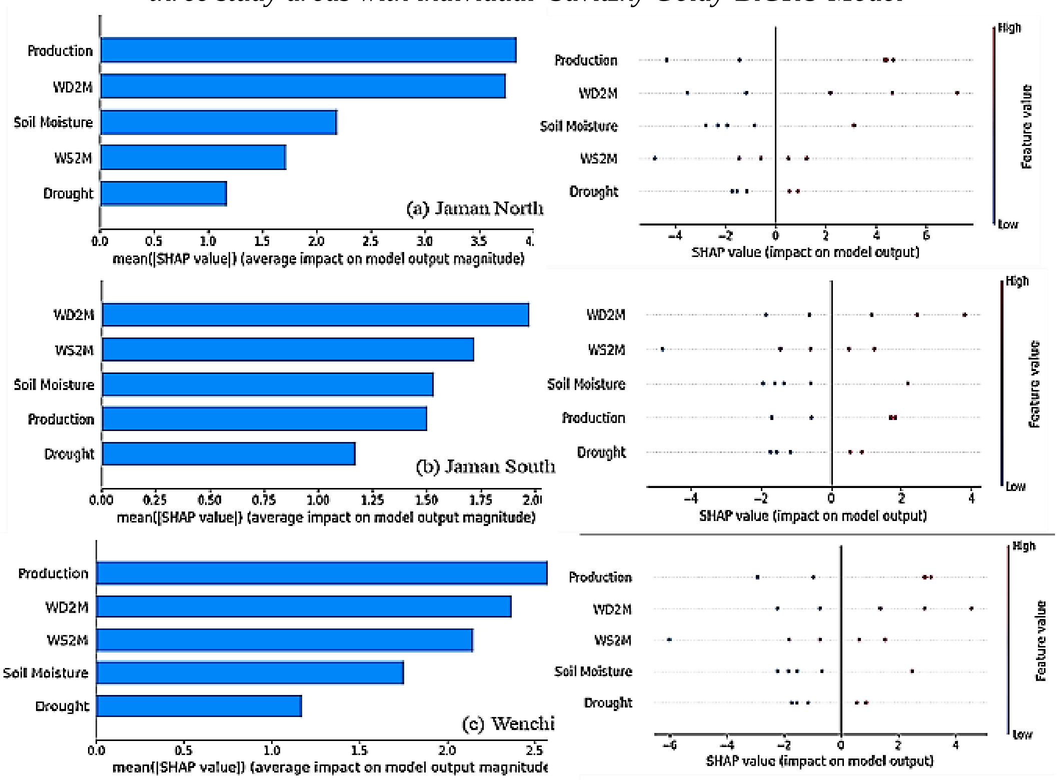

Figure 12. *(a)-(c) SHAP values chart for impact on model output for selected features for the three study areas with individual Savitzky Golay BiGRU Model-Multi-Head Attention Mechanism ensembled model*

The study employs advanced ensemble deep learning models, specifically Bi-directional Gated Recurrent Unit (BiGRU) and Multi-Head Attention Mechanism (MHAtt), combined with data smoothing using the Savitzky Golay method to reduce noise and improve data quality. These innovations collectively improve the precision of cashew yield predictions and provide valuable insights into the integration of wind speed and wind direction as environmental parameters and advanced deep-learning techniques in agricultural forecasting.

Conclusion

This research concentrated on the examination of a dataset concerning cashew production and specific environmental variables, such as wind direction, wind speed, drought, and soil moisture. While previous studies have extensively modeled parameters like drought and soil moisture in crop yield analyses using various statistical, machine learning, and deep learning models, there has been limited attention given to the influence of wind speed and direction on cashew crop yield.

The results obtained from our proposed Savitzky Golay-BiGRU-Multi-Head Attention Mechanism model highlight the significance of data smoothing for subsequent analyses, where the preprocessing provides meaningful trends and rapid variations in time series dataset prediction especially crop yield. Utilizing ensemble deep learning models within a bagging strategy to augment the preprocess capability to enhance computational efficiency. These findings carry positive implications for stakeholders involved in decision-making processes regarding crop yield for sustainable farming. Subsequent research will prioritize the optimization of this model through meta-learning, enabling it to adeptly adjust to new tasks with a reduced set of features, not exclusively confined to wind speed and wind direction to explore predictive powers of other smoothing models fused with learning models.

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