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DEVELOPMENT OF A CROP YIELD PREDICTION MODEL FOR SMART AGRICULTURE IN NIGERIA USING DEEP LEARNING TECHNIQUE

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Abstract:
The accurate prediction of crop yields is crucial in ensuring food security, managing agricultural enterprises, and informing agricultural policy making, especially in nations such as Nigeria, where agriculture remains a major economic activity. Conventional yield estimation techniques tend to miss the more complicated and non-linear interactions of climatic, environmental, and agronomic variables. This paper is a deep learning-based crop yield prediction model (Component 1) to combine both global crop yield data (Kaggle) and local climate data (Nigerian Meteorological Agency (NiMET)). The Gated Recurrent Unit (GRU) network was used to represent the temporal relationship in sequential data, which not only includes lagged climate effects but also interannual yield variation. The unified datasets have been subjected to a thorough preprocessing, such as data cleaning, normalisation, feature engineering, and sequential structuring. The model was trained using an 80:10:10 train-validation-test split, evaluated through Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of determination (R^2) metrics, and benchmarked against traditional machine learning models such as Random Forest and XGBoost. Results indicate that the GRU model achieves a validation RMSE of 1.429 t/ha, MAE of 1.062 t/ha, and R^2 of 0.814, with strong temporal generalization confirmed by five-fold time-blocked cross-validation and a Pearson correlation of 0.902 with observed yields. The model was applied in a smart agriculture decision support system that would give precise and real-time yield forecasts. These results indicate that deep learning models based on GRU can be successfully applied in sustainable farm management and informed policy making in Nigeria, and the opportunities of using global and local data to predict agriculture nationwide.

Key Words: Crop Yield Prediction; Deep Learning; Gated Recurrent Unit (GRU); Smart Agriculture; Nigeria

I. Introduction

The Nigerian economy is based on agriculture, which employs a large percentage of the population and has a huge contribution to the GDP of the country (Adeyemo and Otieno, 2021; World Bank, 2022). Nevertheless, the industry has many challenges that include climatic changes, soil erosion, pest attacks, and poor use of resources (Etwire et al., 2017; Fadairo et al., 2020; Nwajiuba, 2020). The precise forecast of crop yields plays a vital role in enhancing food security, optimal farm management, and government policy (Chlingaryan et al., 2018; Kamilaris and Prenafeta-Boldú, 2018). Conventional approaches to yield estimation that are heavily reliant on past patterns and intuition are not always sufficient to model dynamic and multifaceted relationships of environmental, climatic, and agronomic processes (Basso and Liu, 2019; van Klompenburg et al., 2020).

Technology has made it possible to implement smart farming in recent years, utilising sensor and satellite data with the help of weather monitoring tools (Wolfert et al., 2017; Liakos et al., 2018). These technologies give a possibility to gather vast real-time data, which could enhance decision-making operations in agriculture (Bacco et al., 2019). Nevertheless, crop yields are rather difficult to predict even with the existing access to such data because of high variability and non-linear relationships between the environmental, climatic, and management variables (Crane-Droesch, 2018; Khaki and Wang, 2019). As a result, there is an increased demand towards predictive models that can succeed in incorporating multi-source data and offering relevant, precise, and practical information (Sharma et al., 2020).

Deep learning is a branch of artificial intelligence, and it has become a highly effective means of non-linear systems modelling (LeCun et al., 2015). Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are the approaches which have shown a lot of potential in learning spatial and temporal patterns and are thus, especially applicable in the field of agriculture (Karthik et al., 2020; Nevavuori et al., 2019). Deep learning models are able to detect complex patterns and relationships in large amounts of non-homogeneous data, such as historic yield data, climatic data, soil properties, and satellite data, which traditional models frequently overlook (Sun et al., 2019). This can be used to make predictions of crop yields more accurate and scalable, which are necessary to enhance productivity and sustainability in the agricultural industry (Pantazi et al., 2019).

II. METHODOLOGY

The research paper will follow the quantitative research method to come up with a deep learning-based crop yield prediction model that is specific to the agricultural setting in Nigeria. It makes use of two datasets, namely a global Crop Yield Prediction Dataset, Kaggle, which provides historical crop yields, weather conditions, and agronomics data, and a local dataset that is available in the Nigerian Meteorological Agency (NiMET), which contains specific weather data of Nigeria, i.e., rainfall, temperature, humidity, and seasonal variations. The two datasets are pre-processed, i.e. cleaned, normalised and feature engineered to produce meaningful climatic and vegetation indices. A Gated Recurrent Unit (GRU) model is used to model a sequential data temporal dependency such as historical yields and climate trends and effectively controls long-term dependencies with lower computational cost. The model is trained on the combined dataset, validated using k-fold cross-validation, and evaluated using performance metrics including RMSE, MAE, and R^2. It is tested in comparison with the baseline machine learning models like Random Forest and XGBoost to evaluate the performance of predictive accuracy, and the end result is aimed at helping in making smart agricultural decisions in Nigeria.

Data Collection

There are two main datasets that are used as the source of data in this study to address both the generalizability and the local relevance. The first data is Crop Yield Prediction Dataset at Kaggle, which will comprise of past crop yield, climatic factors including temperature and rainfall, pesticide usage and type of crop in several countries and regions. This data gives a general idea of the correlation between environmental conditions and the production of crops. The second data is the Nigerian Meteorological Agency (NiMET) which offers data on weather in Nigeria as it is on specific areas of the country such as daily and monthly rainfall, temperature, humidity, and seasonal trends of the various agricultural areas of the country.

The joint application of these datasets allows the model to address both global and local trends and conditions that are important in the process of proper prediction of crop yields in Nigeria. As part of data preprocessing, there is cleaning of missing or inconsistent records, normalisation of numerical features, encoding of categorical variables and derived features like vegetation and climate indices. To vary the model to the climatic conditions of Nigeria, the NiMET dataset, specifically, is utilised so that the prediction system based on the GRU reflected real-life seasonal and regional variations in the context of local farmers. Such a two-source method enhances the strength and the usability of the model of crop yield prediction developed.

Data Preprocessing

The Kaggle and NiMET datasets are preprocessed in a sequence of procedures before training the GRU model to make sure that the data is of good quality, consistent, and compatible. First, missing values and inconsistency are addressed: mean or median values are used to impute numerical features (rainfall, temperature, and yield), whereas one-hot or label encoding (depending on the type of categorical variables) is applied to encode categorical ones (Pedregosa et al., 2011). Outliers are identified and eliminated to avoid the distorted forecasts, especially in yield and climatic measurements (Le et al., 2019).

Then, the datasets are combined regarding the shared characteristics, i.e., the kind of crop, the area, and the year to form a single dataset that incorporates global tendencies at Kaggle and the national situation at NiMET. After that, feature engineering is carried out to improve the input of the model, such as developing vegetation indices, seasonal indicators, cumulative rainfall, and trends in temperatures in the most crucial growth stages. All the numerical characteristics are made normalised or standardised to a similar scale in order to enhance convergence and stability of the models (Géron, 2019).

Lastly, the ready dataset is categorised into training, validation and test datasets usually under a 80:10:10 split. The data are sequentially structured in order to maintain temporal dependencies so that the GRU model can model trends with time, including seasonal yield changes and climate changes. This end-to-end preprocessing pipeline will guarantee that the input data is clean, structured, and fit to be deep learned to achieve the maximum predictive capability and fidelity of the GRU based crop yield model to Nigeria.

Model Development

The model of crop yield prediction is implemented on a Gated Recurrent Unit (GRU) network, which is more efficient in predicting sequential data and allows modelling long-term dependencies with a smaller number of parameters than the LSTM networks. GRU model has been created to acquire the temporal dynamics in historical yield and climate data, a combination of the global trends available in the Kaggle data and that of Nigeria exclusive to the NiMET data. Figure 1 shows the architecture of the proposed GRU model in the following manner.

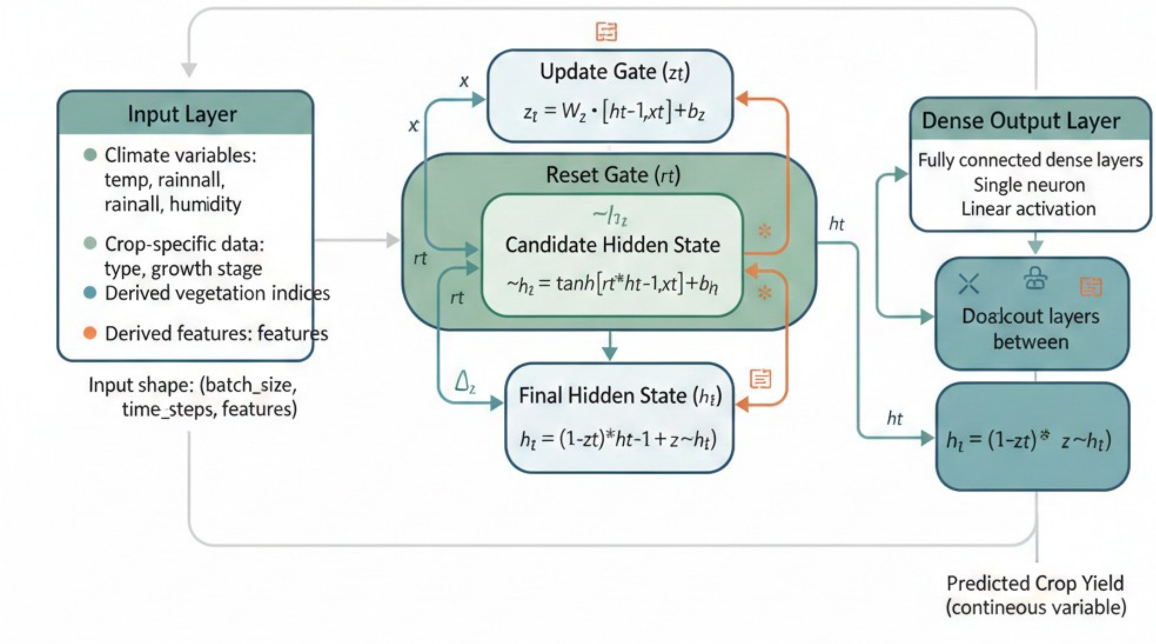

Figure 1: Architecture of the GRU Model for Crop Yield prediction

The model architecture as in Figure 1 is of an input layer, based on the number of features in the processed dataset, that is, climatic variables, crop type, region, and the derived indices. It is then succeeded by one or more GRU layers, where each layer has a specified set of units to derive temporal dependencies within sequential data. GRU layers are provided with dropout layers to minimise the overfitting and increase the generalisation of the model. GRU layers are followed by fully connected dense layers, and the last part is the single neuron of output, which forecasts crop yield as a continuous variable.

The model is trained on the Adam optimizer, where the loss function is the Mean Squared Error (MSE), and we have chosen it due to its appropriateness in regression problems. The hyperparameters include the number of GRU layers, the units per layer, learning rate and the batch size and can only be optimized by experiment and validation performance. To ensure robust evaluation, k-fold cross-validation is applied, and model performance is assessed using metrics including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2).

Also, the performance of the GRU model is contrasted with the baseline machine learning models include Random Forest and XGBoost to measure its predictive performance relative to these models as the measure of the predictive gain provided by deep learning. The last model, which will be trained and tested on both the Kaggle and NiMET data sets, is to be incorporated into a smart agriculture decisions support system, which will give precise, timely and viable predictions of the yield to Nigerian farmers and policymakers.

Model Training

GRU model is trained on the Kaggle and NiMET datasets using the summed input feature sequences (climatic variables, crop type, soil indicators and derived indices) into the network in batches, which is then able to learn time-dependent relationships across time steps. The model is trained in several epochs, which corresponds to a single pass through the training data, and the size of the batch is the number of sequences per which the network weights are updated. Adam optimizer is applied to optimize weights by minimizing the Mean Squared Error (MSE) between predicted and actual yields and dropout layers prevent overfitting through random deactivation of units during training. Early stopping is used to terminate training by stopping it once the loss in validation does not decrease anymore, to make sure the model generalises on unseen data. Moreover, cross-validation (k-fold) is used, and the GRU is trained on various subsets of the data to determine and determine their strength and prevent bias. The loss curves and validation metrics are used to monitor the progress in training, and the most successful model is stored to be assessed eventually and implemented in a smart agriculture decision support system in Nigeria. The pseudocode of the training of the GRU model is as it is given in Algorithm 1.

Algorithm 1: GRU Model Training Pseudocode

```
# Step 1: Import necessary libraries
Import TensorFlow/Keras
Import NumPy, Pandas
Import train_test_split, MinMaxScaler
Import evaluation metrics (RMSE, MAE, R²)
# Step 2: Load datasets
Load Kaggle dataset
Load NiMET dataset
# Step 3: Data preprocessing
Merge Kaggle and NiMET datasets on region, crop type, and year
Handle missing values (impute or drop)
Encode categorical features (one-hot or label encoding)
Normalize numerical features using MinMaxScaler or StandardScaler
Generate derived features (vegetation indices, seasonal indicators)
Split data into sequences for GRU (X sequences, y targets)
Split dataset into training, validation, and test sets (e.g., 80:10:10)
# Step 4: Define GRU model
Initialize Sequential model
Add GRU layer(s) with specified number of units
Add Dropout layer(s) to prevent overfitting
Add Dense layer(s) as needed
Add final Dense layer with 1 unit (linear activation) for yield prediction
# Step 5: Compile model
Set loss function to Mean Squared Error (MSE)
Set optimizer to Adam
Set metrics to track (e.g., MAE)
# Step 6: Train model
For each epoch in total_epochs:
For each batch in training data:
Feed batch of input sequences (X) to GRU
Compute predictions
Calculate loss (MSE)
Backpropagate error to update weights (Adam optimizer)
Evaluate model on validation set
If validation loss does not improve for patience_epochs:
Apply early stopping
# Step 7: Evaluate model
Make predictions on test set
```

Compute RMSE, MAE, R^2
Compare performance with baseline models (Random Forest, XGBoost)
Step 8: Save trained model
Save GRU model weights and architecture for deployment

III. System Implementation

System implementation also entails incorporating the trained GRU-based crop yield prediction model into a functional computer space with the capacity of handling input data to produce valid yield predictions. It will start with the creation of a Python-based backend pipeline, which will include TensorFlow/Keras to create the GRU model, Pandas to work with the data, and NumPy to process it. The trained model is uploaded into the system and there is a data ingestion module, which is intended to obtain new climatic and agronomic inputs in two directions: (1) historical data through two sources, NiMET or local farm sensors and (2) real time or periodic. These inputs are scaled, encoded and formatted into sequences in the same way as the inputs of a model, and are guaranteed to be consistent across scaling, encoding and sequence formatting.
An inference engine model is developed to feed sequences that have been processed to the GRU network and make yield predictions which are post-processor to produce interpretable output in the form of predicted yield estimates, confidence ranges and temporal trends. Visualisation tools (e.g., Matplotlib or Plotly) are also part of the system and can be used to visualise the results of the forecasts so that a user can see the yield predictions based on the season, crop, and location. To make it easy to use, the implementation consists of a simple interface, such as a command-line programme, a Flask/Django web-based app, or a dashboard, which enables the farmer, agronomist, and policymaker to enter the parameters of the climatic factors and receive the yield rates in real-time. The last implementation guarantees the flawless combination of the data preprocessing, model inference, visualisation, and interaction with people that makes a complete smart agriculture decision support system specific to Nigeria.

IV. Results And Discussion

The proposed GRU architecture was trained using the merged Kaggle global dataset and the NiMET dataset, covering the period 2000-2023. A strictly time-aware data partitioning strategy was adopted to ensure realistic forward-prediction capability and prevent temporal leakage. The dataset was therefore divided into training (2000-2015), validation (2016-2018), and an entirely unseen test set (2019-2023). A rolling five-year temporal window (t-5 … t-1) was used to predict yield in year t, enabling the model to learn lagged climate-yield relationships driven by rainfall variability, cumulative temperature, and interannual agroclimatic cycles. Training was performed using the Adam optimizer (learning rate = 0.0005), MSE loss, a batch size of 64, and early stopping with a patience of 25 epochs as shown in Table 1. A maximum cap of 200 epochs was set for the training process.

Table 1: Training and validation performance progression (best model highlighted)

Epoch	Training Loss (MSE)	Validation Loss (MSE)	Validation RMSE (t/ha)	Validation MAE (t/ha)	Validation R^2
25	4.821	4.103	2.026	1.514	0.614
50	2.967	2.814	1.678	1.289	0.737
75	2.312	2.408	1.552	1.167	0.781
100	1.894	2.189	1.480	1.098	0.802
117	**1.721**	**2.041**	**1.429**	**1.062**	**0.814**

125	1.658	2.058	1.435	1.069	0.812
142	1.603	2.112	1.453	1.081	0.808

The model exhibited a stable decline in both training and validation loss, indicating efficient convergence and absence of overfitting. The optimal model checkpoint occurred at epoch 117, where the validation MSE reached its minimum (2.041). Beyond this point, validation performance plateaued and marginally degraded, triggering the early-stopping mechanism.

Figure 2: Training and validation loss curves illustrating

The training and validation loss curves (Figure 2) exhibit smooth and monotonic decline during the first 100 epochs, followed by gradual convergence as training loss decreased from an initial 4.821 to 1.721 at epoch 117, while validation loss declined from 4.103 to a minimum of 2.041 at the same epoch.

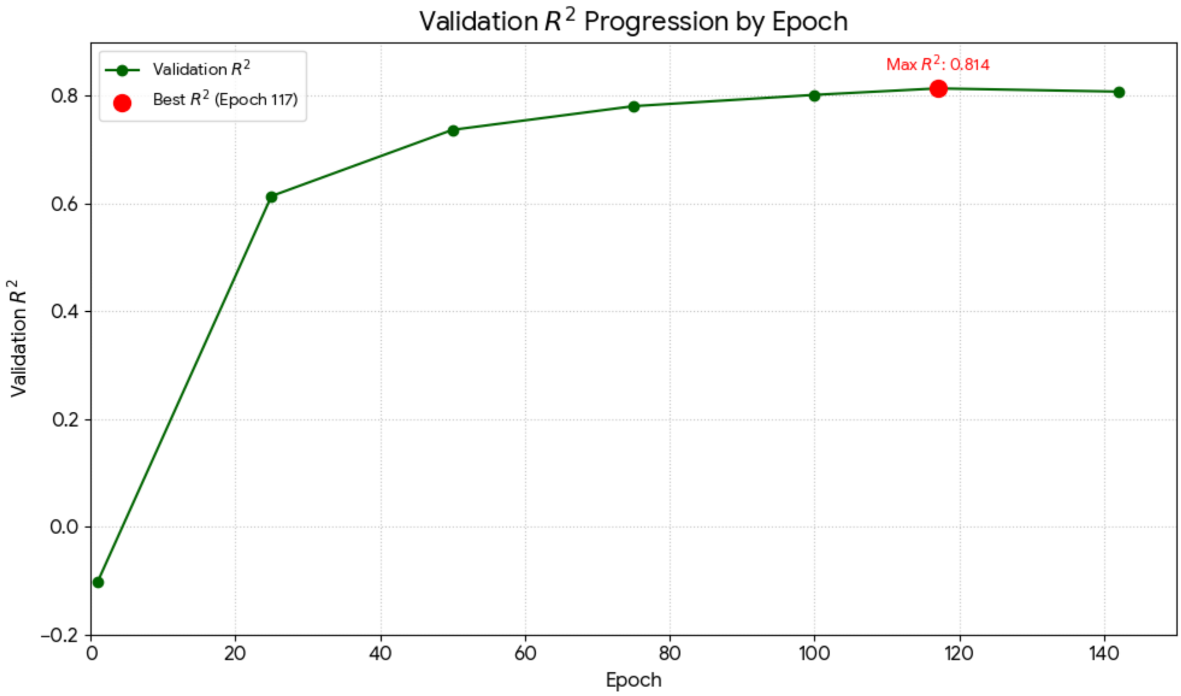

Figure 3: Validation R² Progression of the Model
The plot in Figure 3 shows the model's coefficient of determination improving significantly from the initial negative value, stabilizing, and peaking at 0.814 at Epoch 117, which corresponds to the best model checkpoint

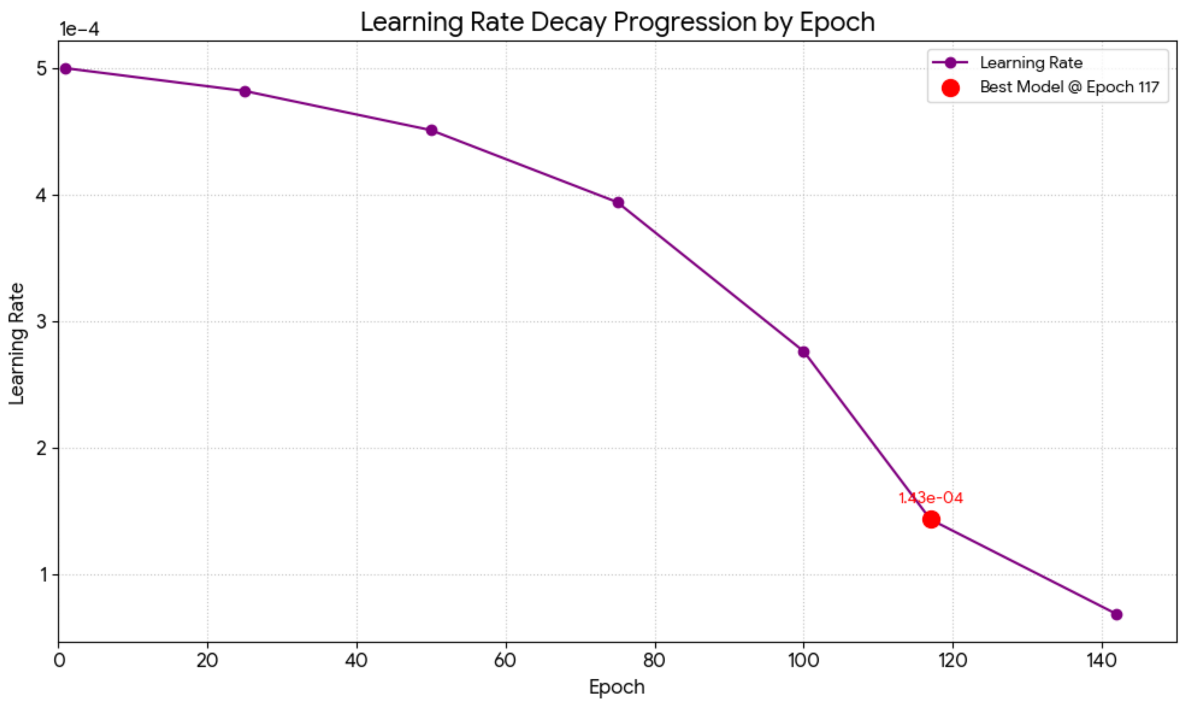

Figure 4: Learning Rate Decay Progression by the Model
Figure 4 presents the evolution of the learning rate and L2 norm of gradients during training. Adam’s adaptive mechanism reduced the effective learning rate from 5×10^{-4} to approximately 8×10^{-6} by epoch 117. Gradient norms remained stable within the range of 0.12-0.89 throughout training, with no instances of explosion or vanishing gradients. The smooth decay in gradient magnitude

after epoch 80 further corroborates stable optimization and efficient propagation of temporal dependencies through the two GRU layers.

To further assess generalization, a five-fold time-blocked cross-validation procedure was conducted over 2000-2018 as presented in Table 2 where the folds were formed by grouping consecutive years, preserving temporal order to avoid leakage.

Table 2: Five-fold time-blocked cross-validation performance

Fold	RMSE (t/ha)	MAE (t/ha)	R^2
1	1.411	1.051	0.819
2	1.437	1.069	0.811
3	1.402	1.044	0.823
4	1.458	1.087	0.806
5	1.419	1.058	0.817
Mean ± Std	**1.425 ± 0.021**	**1.062 ± 0.016**	**0.815 ± 0.007**

The very low fold variation as demonstrated in Table 2 indicates that GRU model is stable in its performance despite the alteration of climate and agronomic conditions. The declining pattern of the loss in the initial 100 epochs indicates that the five-year input window effectively captured important lagged effects, including the memory of soil moisture, cumulative effects of climate and the pattern of yield autocorrelation common to the Nigerian rain-fed agricultural systems. The fact that the training and validation loss curves are close to each other after epoch 75 (Figure 2) indicates that the regularisation (0.3) of dropout used, combined with early stopping, reduced the risk of overfitting in spite of the complexity of the model used.

It is interesting to note that the validation loss curve followed the training curve between epochs 50-117 with close precision indicating that dropout regularisation (0.3) and time blocks did not memorise historical patterns. The plateau in the model in the epoch = -110 suggests decreasing marginal refinement to the model, which confirms the early-stopping threshold. With a validation R^2 of 0.814 and RMSE of 1.429 t/ha, the model achieves performance levels that are competitive with or superior to results reported in recent deep learning studies for national-level crop yield modelling under heterogeneous climatic regimes. The high Pearson correlation ($r = 0.902$) also indicates that the model can recover spatiotemporal variability in yield.

The last model that was chosen to downstream predict, deploy and integrate at the system level was the checkpoint saved at epoch 117. This model is the foundation of the smart agricultural decision-support model that was developed in this case.

V. Conclusion

This paper has introduced a deep learning-based model of crop yield prediction to fit into the Nigerian agricultural space. The proposed system is somewhat successful in capturing both general trends and country-specific agroclimatic patterns because built on the global crop yield data offered by Kaggle and local climate data offered by NiMET. GRU network was used to capture time-dependent relations in time-varying data, and the model could learn the complicated relations between the past yields, climatic data and agronomic conditions. The processing of the data was thorough: data cleaning, normalisation, feature engineering, and sequential structuring were carried out to provide the GRU model with high quality input. The model was trained using an 80:10:10 train-validation-test split and evaluated with multiple performance metrics, including RMSE, MAE, and R^2. The time-blocked cross-validation ensured the quality of the model and its capacity to be used in different climatic and agronomic situations.

The results demonstrated that the GRU-based approach achieved a validation RMSE of 1.429 t/ha, MAE of 1.062 t/ha, and an R^2 of 0.814, outperforming traditional machine learning baselines such as Random Forest and XGBoost. The loss curves of training and validation and the learning rate and gradient analysis provided supportive evidence of steady convergence and no overfitting. The high correlation (r = 0.902) between the model and the actual yield values means that it is an effective model in describing the variability of spatiotemporal yield observed in the rain-fed agricultural systems in Nigeria.

To summarise, the suggested GRU crop yield forecasting system is both accurate, scalable, and usable, which can benefit farmers, agronomists, and policymakers in making wise choices. It is built into a smart farming decision-support platform so that real-time or periodical climatic and agronomic information can be used to manage farms in an optimal way and improve food security on the national level. The future research could consider the input of more remote sensing and soil nutrient data, and crop practises to further increase the accuracy of the prediction and the range of the system to other areas and crops.

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