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Comparative Performance of Machine Learning and Deep Learning Algorithms for Agricultural Land Mapping in Anambra State, Nigeria

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Abstract - Accurate delineation of agricultural land is fundamental to agricultural planning, food-security assessment, land-resource management, and monitoring of land-use transformation. However, the heterogeneous and fragmented character of agricultural landscapes in southeastern Nigeria presents substantial challenges for satellite-image classification. This study comparatively evaluated Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN) for agricultural land mapping in Anambra State, Nigeria. Remotely sensed imagery was classified into waterbody, dense forest, agricultural land, built-up area, and bare ground using the four algorithms. Model performance was evaluated using 210 validation samples and multiple confusion-matrix metrics, including sensitivity, precision, specificity, negative predictive value, overall accuracy, balanced accuracy, and Matthew's correlation coefficient. Agricultural land estimates varied from 1,000.26 km² (21.78%) for SVM to 1,099.12 km² (23.93%) for ANN. SVM achieved the strongest overall performance, recording 88.5% sensitivity, 85.2% precision, 75.0% specificity, 83.3% overall accuracy, 81.7% balanced accuracy, and a Matthews correlation coefficient of 0.643. CNN produced the lowest overall accuracy of 74.3%. The findings demonstrate that increased model complexity does not necessarily translate into superior classification performance and establish SVM as an effective approach for regional agricultural land delineation under heterogeneous tropical landscape conditions.

Keywords: agricultural land mapping; machine learning; deep learning; Support Vector Machine; Random Forest; artificial neural network; convolutional neural network; remote sensing

1. Introduction

Reliable information on the location and extent of agricultural land supports agricultural planning, food-security assessment, environmental monitoring, and sustainable land management. Satellite remote sensing provides repeatable spatial observations that allow agricultural landscapes to be mapped more efficiently than conventional field-based inventories across extensive areas (Weiss et al., 2020; Liakos et al., 2018). Nevertheless, converting remotely sensed observations into reliable thematic information remains challenging because classification performance depends on image characteristics, feature selection, training samples, landscape heterogeneity, and the classifier employed (Lu and Weng, 2007; Maxwell et al., 2018).

Machine-learning algorithms have consequently become prominent in land-cover and agricultural mapping. Random Forest (RF) combines multiple decision trees and performs effectively with high-dimensional data, nonlinear relationships, and correlated predictor variables (Pal, 2005; Gislason et al., 2006; Belgiu and Drăguț, 2016). Support Vector Machine (SVM), conversely, constructs optimal separating boundaries and has demonstrated strong generalisation with relatively limited training samples, making it particularly relevant to remote-sensing applications (Huang et al., 2002; Mountrakis et al., 2011). Comparative agricultural-landscape research has further demonstrated that RF and SVM can provide strong classification performance, although their relative effectiveness varies with data characteristics and classification design (Duro et al., 2012; Maponya et al., 2020).

Advances in computational capacity have expanded remote-sensing classification towards Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs). ANNs can model complex nonlinear relationships between remotely sensed features and land-cover classes, while CNNs additionally exploit spatial and contextual information through hierarchical feature extraction (Kavzoglu and Mather, 2003; Chen et al., 2014; Yue et al., 2015; Zhu et al., 2017). Deep architectures therefore offer considerable potential for remote-sensing image classification, but their effectiveness is influenced by training-data quantity, landscape structure, spatial resolution, architecture, and the correspondence between learned features and target classes. Consequently, greater algorithmic complexity should not automatically be interpreted as greater mapping accuracy.

These considerations are especially relevant in sub-Saharan Africa. Agricultural landscapes are frequently characterised by small fields, fragmented cropland, mixed cropping, fallow vegetation, variable crop calendars, and spectral mixing between agricultural and surrounding vegetation. Xiong et al. (2017) identified heterogeneous and fragmented landscapes and limited reference information as major difficulties in African cropland mapping, while Rufin et al. (2022) similarly demonstrated the difficulty of distinguishing active cropland and fallow land in smallholder systems. Nigerian research has further demonstrated the challenge of mapping smallholder and intercropped agricultural systems from satellite imagery (Kerner et al., 2021).

Research within Anambra State has compared conventional supervised classification techniques. Ejikeme et al. (2019), for example, evaluated Maximum Likelihood, Minimum Distance, Mahalanobis Distance, Spectral Angle Mapper, and Parallelepiped classifiers for land-use/land-cover mapping in Awka South. However, limited empirical evidence directly compares conventional machine-learning methods with neural-network and deep-learning approaches for agricultural-land delineation across Anambra State. Moreover, reliance on overall accuracy alone may conceal differences in omission and commission errors. Accuracy assessment literature therefore recommends examining complementary class-specific and confusion-matrix-derived measures rather than interpreting a single statistic in isolation (Congalton, 1991; Stehman, 1997; Olofsson et al., 2014; Foody, 2020).

This study addresses these gaps by comparatively evaluating RF, SVM, ANN, and CNN for agricultural land mapping in Anambra State. Specifically, it determines agricultural-land extent produced by each classifier and evaluates their performance using sensitivity, precision, specificity, negative predictive value, overall accuracy, balanced accuracy, and Matthew's correlation coefficient. The comparison provides empirical evidence on whether neural-network complexity translates into improved agricultural-land classification within a heterogeneous tropical landscape and provides a basis for selecting appropriate algorithms for regional agricultural mapping and land-management applications.

2. Materials and Methods

2.1 Study Area

Anambra State is located in southeastern Nigeria and occupies approximately 4,416 km². The state is bounded by Enugu State to the east, Kogi State to the north, Delta State to the west, and Imo and Abia States to the south. Its landscape comprises relatively low-lying plains, rolling terrain, river valleys, forest remnants, agricultural areas, and extensively developed settlements. The climate is humid tropical, with annual rainfall of approximately 1,520–2,030 mm. Agriculture constitutes an important component of land use, with crops including cassava, yam, maize, rice, and oil palm. Rapid settlement expansion, fragmented cultivation, fallow vegetation, and forest-agriculture transitions create heterogeneous land-cover conditions that make Anambra State suitable for evaluating alternative remote-sensing classification algorithms.

2.2 Research Design and Satellite Data Processing

The study adopted a comparative remote-sensing classification framework to evaluate the effectiveness of conventional machine-learning and neural-network algorithms for agricultural land mapping. Four supervised classifiers comprising Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN) were independently applied to remotely sensed satellite imagery covering Anambra State. Similar comparative frameworks have been employed to determine how alternative classifiers respond to variations in agricultural landscapes and remotely sensed predictor information.

The satellite imagery was prepared to establish a consistent dataset covering the study area. Pre-processing involved geometric alignment, removal of unsuitable image portions, image compositing where required, and clipping to the Anambra State administrative boundary. Spectral information contained in the processed imagery constituted the predictor information for land-use classification. The image dataset and reference observations were subsequently organized to ensure that the same geographical coverage and class definitions were used across the four algorithms. This common input framework reduced the possibility that differences among the resulting maps originated from differences in input data rather than classifier behaviour.

2.3 Definition of Land-Use Classes and Reference Samples

Five land-use and land-cover classes were defined as waterbody, dense forest, agricultural land, built-up area, and bare ground. Agricultural land represented the target class because the primary purpose was to determine how effectively each algorithm could identify agricultural areas within the heterogeneous landscape. The remaining classes represented major land-cover conditions against which agricultural land had to be discriminated. Representative samples were assigned to the respective classes using reference information derived from identifiable land-cover characteristics. Sample selection sought to capture the spectral and spatial variability occurring within each class. Appropriate representation of within-class variability is important because training-data quantity and composition can substantially influence agricultural classification performance. The reference observations were separated from those subsequently employed for independent performance evaluation to prevent model assessment using observations involved in model development.

2.4 Image Classification

RF, SVM, ANN, and CNN were applied independently to the prepared imagery. RF classified pixels through an ensemble of decision trees constructed from subsets of the training observations and predictor variables. Individual tree decisions were aggregated to produce the final class assignment. SVM differentiated the land-use classes by constructing decision boundaries that maximized separation within the multidimensional feature space. Its ability to handle complex class boundaries makes it particularly applicable where agricultural vegetation exhibits spectral similarities with forest, fallow, or other vegetated surfaces. ANN was implemented to capture nonlinear relationships between remotely sensed input features and the predefined land-use classes. CNN extended this learning process by incorporating spatial patterns associated with neighbouring image information, allowing hierarchical spatial and spectral features to contribute to classification. CNN-based approaches have increasingly been applied to agricultural land-use classification because convolutional operations can identify contextual patterns that conventional pixel-based classifiers may not capture directly. Each classifier produced a complete thematic map containing the five predefined classes.

2.5 Agricultural Land Extraction and Area Estimation

Agricultural land was extracted independently from each classified output to determine the influence of classifier selection on estimated agricultural extent. Pixel counts belonging to agricultural land were converted to area and subsequently expressed as percentages of the total mapped study area. The same procedure was applied to waterbody, dense forest, built-up area, and bare ground to permit comparison of the overall distribution of classes. This stage enabled comparison beyond classification accuracy by determining whether the algorithms produced materially different estimates of agricultural land. Such comparison was particularly relevant because mixed pixels, fragmented farms, settlement-agriculture interfaces, forest margins, and fallow areas can affect cropland delineation in heterogeneous agricultural landscapes. Recent studies have demonstrated that spatial fragmentation and mixed spectral responses remain important sources of uncertainty in agricultural land identification.

2.6 Classification Performance Assessment

An independent set of 210 validation samples was used to assess classification performance. For the specific evaluation of agricultural-land detection, the five-class results were transformed into a binary assessment consisting of agricultural land and non-agricultural land. The validation dataset contained 130 actual agricultural samples and 80 non-agricultural samples. Predictions from each classifier were compared with the corresponding reference observations to obtain true positives, true negatives, false positives, and false negatives.

Performance was evaluated using sensitivity, precision, specificity, negative predictive value, overall accuracy, balanced accuracy, and Matthew's correlation coefficient. Sensitivity measured the proportion of actual agricultural observations correctly identified, whereas precision represented the reliability of predicted agricultural observations. Specificity assessed correct discrimination of non-agricultural observations, while negative predictive value measured the reliability of predictions assigned to the non-agricultural category. Overall accuracy quantified the proportion of all validation observations correctly classified.

Balanced accuracy was included to account for differences in the number of agricultural and non-agricultural validation observations. Matthew's correlation coefficient provided an additional integrated measure incorporating all components of the binary confusion matrix. Reliance on several complementary measures allowed model performance to be interpreted from both agricultural detection and non-agricultural exclusion perspectives rather than from overall accuracy alone.

2.7 Comparative Analysis of Classifiers

The four classifiers were finally compared using their estimated agricultural area and complete set of validation metrics. Particular attention was given to the relationship between sensitivity and specificity to determine whether individual models favored agricultural-land detection at the expense of increased false-positive classifications. Precision was considered alongside sensitivity to identify possible overprediction of agricultural land. Balanced accuracy and Matthew's correlation coefficient were used to assess overall consistency across agricultural and non-agricultural observations. The combined evaluation therefore considered both spatial output and predictive performance. This approach permitted assessment of whether the additional representational capacity of ANN and CNN produced measurable improvements over RF and SVM under the data and landscape conditions of Anambra State. Comparative agricultural remote-sensing studies demonstrate that greater model complexity does not invariably produce superior classification because performance also depends on training data, spatial resolution, temporal information, class structure, and landscape characteristics.

3. Results

3.1 Classification and Identification of Agricultural Land Use Using Machine Learning Algorithms

The first objective of this study focused on the classification and identification of agricultural land use in Anambra State through the application of four machine learning algorithms, namely Random Forest, Support Vector Machine, Artificial Neural Network, and Convolutional Neural Network, using remotely sensed satellite imagery. The classification process produced five major land use classes, comprising Waterbody, Dense Forest, Agricultural Land, Built-Up Area, and Bare ground.

Random Forest classification yielded an agricultural land area of 1034.79 km², representing 22.53 % of the study area. Support Vector Machine produced a slightly lower estimate of 1000.26 km² (21.78 %), whereas the Artificial Neural Network model classified 1099.12 km² (23.93 %) as agricultural land. The Convolutional Neural Network model identified 1062.93 km², corresponding to 23.14 % of the area (Table 1). These spatial extents reflect differences in algorithmic sensitivity to spectral and spatial features inherent in the satellite data.

Table 1: Land Use Classification Result Using Random Forest

Land Use Class	Area (km ²)	Percentage (%)
Waterbody	96.34	2.10
Dense Forest	1517.69	33.05
Agricultural Land	1034.79	22.53
Built-Up Area	1928.88	42.00
Bare ground	14.79	0.32

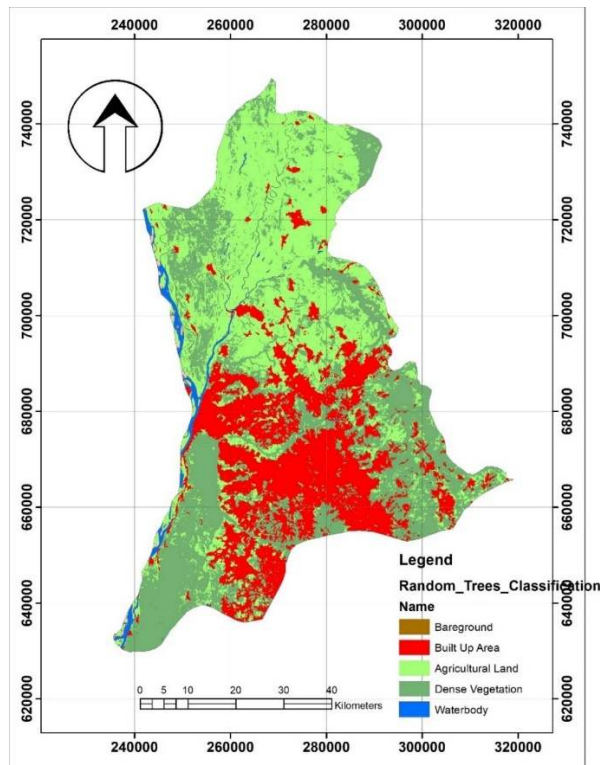


Figure 1: Random Trees Classification

Support Vector Machine classification (table 2) produced an agricultural land extent of 1000.26 km², representing 21.78 % of the study area. Dense forest and built-up areas remained the dominant classes. The slightly lower agricultural land estimate relative to Random Forest indicates stricter class boundary delineation by the SVM decision function.

Table 2: Land Use Classification Result Using Support Vector Machine

Land Use Class	Area (km ²)	Percentage (%)
Waterbody	98.14	2.14
Dense Forest	1597.21	34.78
Agricultural Land	1000.26	21.78
Built-Up Area	1878.69	40.91
Bare ground	18.19	0.40

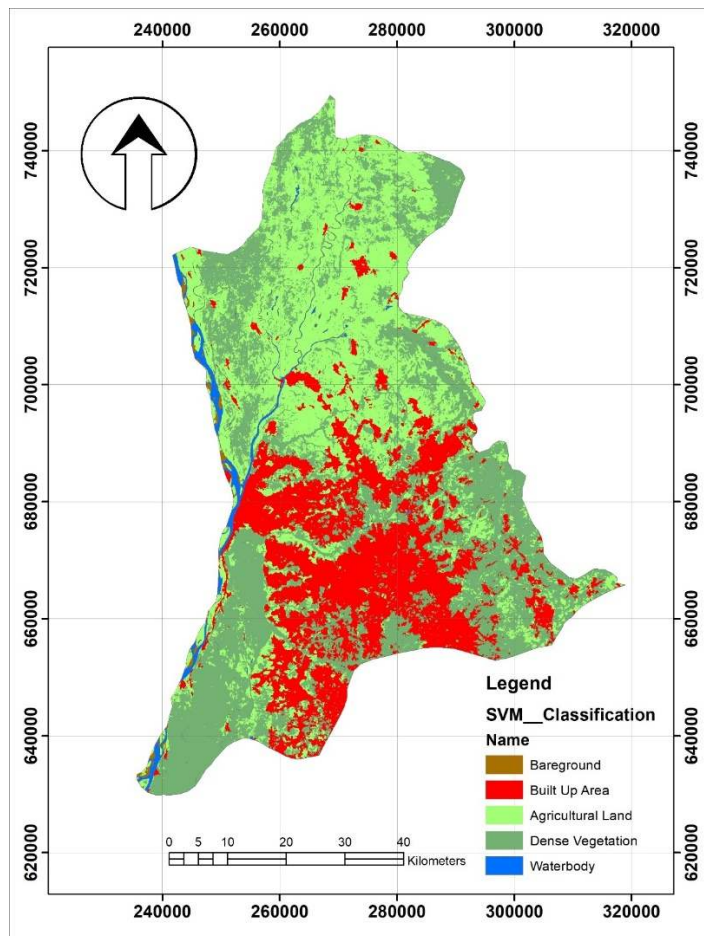


Figure 4.2: Support Vector Machine Classification

The Artificial Neural Network model (table 3) classified agricultural land as covering 1099.12 km², equivalent to 23.93 % of the total area. This represents the highest agricultural land estimate among the four algorithms. The increased extent may be linked to the ANN's capacity to learn complex non-linear relationships between spectral inputs and land use classes.

Table 3: Land Use Classification Result Using Artificial Neural Network

Land Use Class	Area (km ²)	Percentage (%)
Waterbody	100.39	2.19
Dense Forest	1569.55	34.18
Agricultural Land	1099.12	23.93
Built-Up Area	1807.20	39.35
Bare ground	16.23	0.35

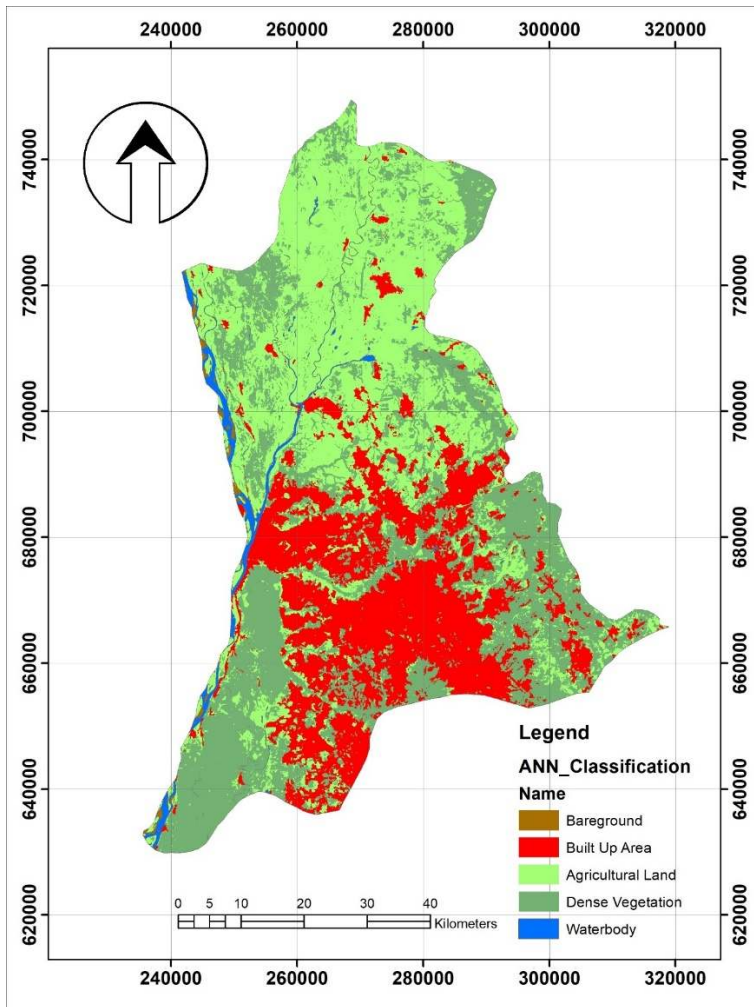


Figure 3: Artificial Neural Network Classification

The Convolutional Neural Network (table 4) classified agricultural land as 1062.93 km², accounting for 23.14 % of the study area. The CNN result closely aligns with the ANN outcome, although with a slightly lower agricultural land proportion. The incorporation of spatial context through convolutional filters enables improved recognition of land use patterns beyond pixel-based spectral information.

Table 4: Land Use Classification Result Using Convolutional Neural Network

Land Use Class	Area (km ²)	Percentage (%)
Waterbody	99.39	2.16
Dense Forest	1519.36	33.08
Agricultural Land	1062.93	23.14
Built-Up Area	1893.58	41.23

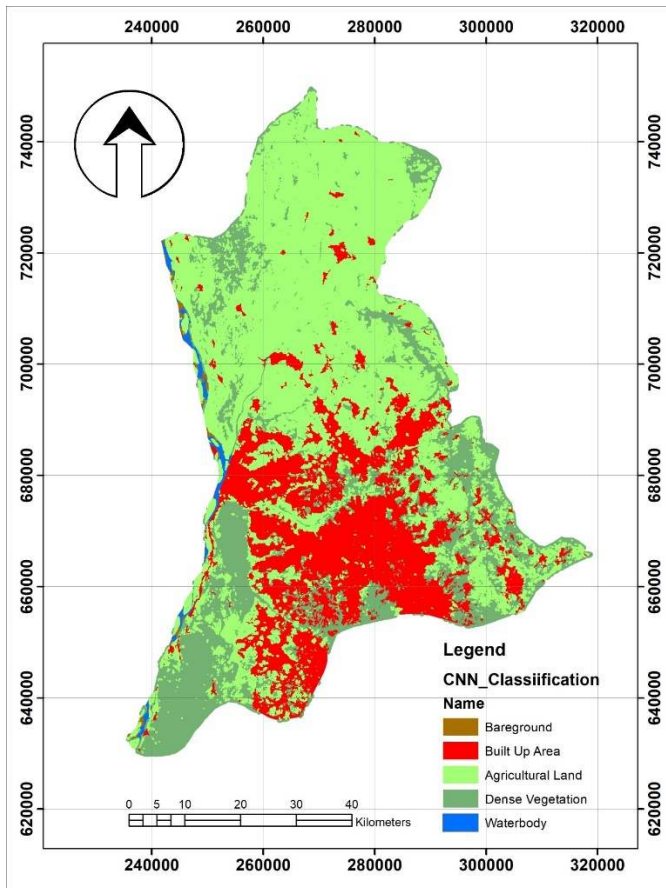


Figure 4: Convolution Neural Network Classification

Comparative analysis of the classification outcomes indicated that all four machine learning algorithms effectively distinguished the agricultural land use class from other land cover categories. Traditional machine learning classifiers such as Random Forest and Support Vector Machine have been widely applied in supervised land use and land cover classification due to their capacity to produce reliable results with varied feature spaces. Random Forest, an ensemble of decision trees, demonstrates robustness against noise and overfitting while accommodating high dimensional input, which facilitates consistent differentiation among heterogeneous land cover types. Support Vector Machine employs a maximum margin classifier that excels at handling non-linear class boundaries through kernel transformations, making it suitable for complex remote sensing datasets.

Neural network-based approaches, specifically Artificial Neural Networks and Convolutional Neural Networks, represent advanced paradigms in remote sensing classification. These models learn multi-layered non-linear representations of spectral and spatial patterns, enabling them to capture intricate relationships among input features those traditional techniques may not explicitly model. Convolutional Neural Networks incorporate spatial convolutional filters that automatically extract hierarchical textural and contextual features from imagery, which can enhance discrimination among land use categories exhibiting complex spatial structures; empirical evidence indicates that CNNs often achieve higher classification accuracies relative to traditional machine learning algorithms in multi-class land cover tasks.

In the context of this study, both neural network approaches (ANN and CNN) classified slightly larger extents of agricultural land compared to Random Forest and SVM. This may be attributed to improved discrimination of mixed or transitional pixels that constitute agricultural boundaries, given the capacity of deep learning models to leverage local spatial dependencies and multi-scale feature extraction. The relative consistency across the four models, however, underscores the reliability of machine learning-based remote sensing classification for delineating agricultural land use patterns in Anambra State. The classification outputs form the basis for subsequent spatial analyses aimed at monitoring land use dynamics and informing agricultural planning.

3.2 Assess the Performance of the Classification

The second objective of this study evaluated the performance of the Random Forest, Support Vector Machine, Artificial Neural Network, and Convolutional Neural Network classifiers using confusion-matrix-derived accuracy indices. The assessment was based on a total of 210 validation samples, comprising 130 actual positive samples representing agricultural land and 80 actual negative samples representing non-agricultural land. Performance evaluation employed sensitivity, precision, specificity, negative predictive value, overall accuracy, balanced accuracy, and the Matthews correlation coefficient, which together provide a robust appraisal of classification reliability for imbalanced land use datasets commonly encountered in remote sensing applications.

3.2.1 Performance Indices for Random Forest Classification

The Random Forest classifier recorded a true positive count of 110 and a true negative count of 50, with 30 false positives and 20 false negatives. The sensitivity value of 0.846 indicates a strong capacity to correctly identify agricultural land pixels, while the precision of 0.786 reflects moderate confidence in the positive predictions. The specificity of 0.625 indicated a comparatively weaker discrimination of non-agricultural land. Overall classification accuracy was 0.762, with a balanced accuracy of 0.736, highlighting moderate consistency across both positive and negative classes. The Matthews correlation coefficient of 0.485 indicates a moderate positive correlation between predicted and observed classes.

Table 5: Performance Indices for Random Forest Classification

Index	Value
Sensitivity	0.846
Precision	0.786
Specificity	0.625
Negative Predictive Value	0.714
Accuracy	0.762
Balanced Accuracy	0.736
Matthews Correlation Coefficient	0.485

The Support Vector Machine classifier achieved the highest overall performance among the evaluated models, with 115 true positives and 60 true negatives, alongside reduced false positive and false negative counts. Sensitivity was 0.885, indicating strong agricultural land detection capability, while precision reached 0.852, reflecting reliable positive class predictions. Specificity and negative predictive value were 0.750 and 0.800, respectively, demonstrating improved separation of non-agricultural areas. Overall accuracy was 0.833, with a balanced accuracy of 0.817. The Matthews correlation coefficient of 0.643 signifies a strong agreement between predicted and reference data.

Table 6: Performance Indices for Support Vector Machine Classification

Index	Value
Sensitivity	0.885
Precision	0.852
Specificity	0.750
Negative Predictive Value	0.800
Accuracy	0.833
Balanced Accuracy	0.817
Matthews Correlation Coefficient	0.643

The Artificial Neural Network model recorded 112 true positives and 48 true negatives, with comparatively higher false positive counts. Sensitivity was 0.862, indicating effective identification of agricultural land, while precision declined to 0.778, reflecting reduced certainty in positive predictions. Specificity was 0.600, and the negative predictive value was 0.727. Overall accuracy matched that of the Random Forest classifier at 0.762, with a balanced accuracy of 0.731. The Matthews correlation coefficient of 0.483 indicates moderate classification consistency.

Table 7: Performance Indices for Artificial Neural Network Classification

Index	Value
Sensitivity	0.862
Precision	0.778
Specificity	0.600
Negative Predictive Value	0.727
Accuracy	0.762
Balanced Accuracy	0.731
Matthews Correlation Coefficient	0.483

The Convolutional Neural Network classifier yielded 113 true positives and 43 true negatives, accompanied by the highest false positive count among the models. Sensitivity was 0.869, indicating reliable agricultural land detection, whereas precision was 0.753, reflecting reduced confidence in positive classifications. Specificity was 0.538, and the negative predictive value was 0.717. Overall accuracy was 0.743, with a balanced accuracy of 0.703. The Matthews correlation coefficient of 0.437 indicates moderate predictive agreement.

Table 8: Performance Indices for Convolutional Neural Network Classification

Index	Value
Sensitivity	0.869
Precision	0.753
Specificity	0.538
Negative Predictive Value	0.717
Accuracy	0.743
Balanced Accuracy	0.703
Matthews Correlation Coefficient	0.437

The disparity observed between sensitivity and specificity across all four classifiers (table 5 – 8) indicates a systematic tendency toward improved detection of agricultural land relative to non-agricultural classes. Higher sensitivity values suggest that the models were effective in minimizing omission errors associated with agricultural land, while comparatively lower specificity values reveal greater commission errors where non-agricultural areas were incorrectly classified as agricultural. This pattern reflects the spectral and structural complexity of the study area, where agricultural land frequently exhibits transitional characteristics with forest margins, fallow plots, and peri-urban vegetation.

The relationship between sensitivity and precision further explains the error structure of each classifier. The Support Vector Machine exhibited a balanced combination of high sensitivity and high precision, indicating reliable identification of agricultural land while maintaining control over false positive classifications. In contrast, the Artificial Neural Network and Convolutional Neural Network demonstrated high sensitivity but reduced precision, implying a propensity to overestimate agricultural land extent. This behaviour indicates that the neural network-based models were more inclined to classify spectrally mixed or fragmented land parcels as agricultural, particularly in areas undergoing active land use transitions.

The Matthews correlation coefficient provides an integrated measure of classification reliability that accounts for both correct and incorrect predictions across classes. The higher coefficient recorded for the Support Vector Machine indicates stronger agreement between predicted and reference data when compared to the other models. Moderate coefficient values for Random Forest, Artificial Neural Network, and Convolutional Neural Network suggest that although these classifiers performed adequately, their predictions were more affected by class overlap and misclassification, particularly for non-agricultural land.

Balanced accuracy results reinforce these observations by highlighting differences in class-wise consistency. The Support Vector Machine achieved the highest balanced accuracy, reflecting relatively uniform performance across both agricultural and non-

agricultural classes. Lower balanced accuracy values for the neural network-based models indicate uneven performance, with stronger emphasis on agricultural land detection than on accurate exclusion of other land use classes. This outcome implies that deep learning approaches did not uniformly enhance classification performance under the data and spatial resolution conditions of this study.

From an application perspective, the results suggest that classifiers with higher specificity, such as Support Vector Machine and Random Forest, are more suitable for analyses requiring reliable delineation of non-agricultural areas, including monitoring land conversion and urban expansion. Conversely, classifiers with higher sensitivity, particularly Artificial Neural Network and Convolutional Neural Network, are advantageous for applications where comprehensive identification of agricultural land is required and underestimation poses greater risk.

3.3 Discussion of Results

The comparative classification results demonstrate that algorithm selection influenced both the estimated extent of agricultural land and the reliability with which agricultural and non-agricultural areas were differentiated. Agricultural land ranged from 1,000.26 km² (21.78%) under Support Vector Machine (SVM) to 1,099.12 km² (23.93%) under Artificial Neural Network (ANN), while Random Forest (RF) and Convolutional Neural Network (CNN) produced intermediate estimates of 1,034.79 km² (22.53%) and 1,062.93 km² (23.14%), respectively. These differences indicate that agricultural area estimates are partly dependent on classifier behaviour rather than representing an invariant property of the satellite data. Similar variability has been reported in agricultural landscape classification, where different machine-learning algorithms produce different class boundaries because of their contrasting treatment of spectral heterogeneity and decision spaces (Duro et al., 2012; Maxwell et al., 2018).

SVM provided the strongest overall performance, achieving sensitivity of 0.885, precision of 0.852, specificity of 0.750, overall accuracy of 0.833, balanced accuracy of 0.817, and Matthew's correlation coefficient (MCC) of 0.643. This result is consistent with the recognised capacity of SVM to establish effective decision boundaries in high-dimensional remote-sensing feature spaces and to generalise effectively when training observations are limited (Mountrakis et al., 2011). The performance also supports findings from agricultural landscape research demonstrating the effectiveness of SVM alongside other established machine-learning classifiers (Duro et al., 2012; Maponya et al., 2020).

RF achieved an overall accuracy of 0.762 and balanced accuracy of 0.736, indicating reasonably effective agricultural-land discrimination but weaker performance than SVM. RF remains widely applicable because of its capacity to accommodate high-dimensional data, nonlinear relationships, and correlated variables while exhibiting relatively low sensitivity to overfitting (Belgiu and Drăguț, 2016). Its specificity of 0.625, however, indicates that confusion between agricultural land and other land-cover categories was more pronounced than under SVM.

A particularly notable outcome concerns the neural-network classifiers. ANN and CNN identified larger agricultural extents and maintained relatively high sensitivities of 0.862 and 0.869, respectively, but their specificity values declined to 0.600 and 0.538. Their combination of high sensitivity and lower specificity suggests that both algorithms captured a large proportion of genuine agricultural locations while simultaneously assigning more non-agricultural observations to the agricultural class. Such behaviour provides a plausible explanation for their larger agricultural-area estimates. Agricultural land in Africa commonly occurs within heterogeneous, fragmented landscapes containing small fields, fallows, mixed vegetation and complex cropping patterns, which complicate spectral discrimination (Xiong et al., 2017).

CNN recorded the lowest overall accuracy (0.743), balanced accuracy (0.703), and MCC (0.437), despite the theoretical capacity of deep-learning architectures to learn complex spatial representations. This finding demonstrates that greater algorithmic complexity did not automatically improve classification under the data conditions of the present study. Deep-learning performance remains dependent on factors such as available training information, input characteristics, model architecture and the suitability of learned representations for the classification problem (Zhu et al., 2017). Likewise, ANN performance depends substantially on network configuration and training characteristics (Kavzoglu and Mather, 2003).

The combined accuracy measures provide stronger evidence than overall accuracy alone. SVM's MCC of 0.643 was substantially higher than RF (0.485), ANN (0.483), and CNN (0.437). MCC incorporates true-positive, true-negative, false-positive and false-

negative outcomes and can therefore provide informative evaluation of binary classification performance (Chicco and Jurman, 2020). The accompanying precision, sensitivity, specificity and balanced accuracy similarly expose differences that a single accuracy statistic could conceal. Foody (2020) advocates greater reliance on interpretable class-specific accuracy measures rather than routine use of chance-corrected kappa statistics.

The findings consequently have implications for agricultural area estimation. Direct calculation of class area from classified maps can inherit classification errors, meaning differences in mapped agricultural extent should not automatically be interpreted as differences in actual agricultural area. Olofsson et al. (2014) recommend integrating reference-sample information with accuracy and area estimation procedures to account for classification uncertainty. The present results therefore identify SVM as the most consistent classifier under the evaluated conditions while demonstrating that agricultural mapping should consider error structure alongside mapped area.

4. Conclusion and Recommendations

4.1 Conclusion

This study comparatively evaluated Random Forest, Support Vector Machine, Artificial Neural Network, and Convolutional Neural Network for remotely sensed agricultural land mapping in Anambra State, Nigeria. The analysis demonstrates that classifier choice affects not only predictive performance but also the estimated spatial extent of agricultural land. Agricultural area varied by approximately 98.86 km² between the lowest estimate produced by SVM and the highest estimate produced by ANN. Such variation is sufficiently substantial to influence interpretations of agricultural land availability when classified maps are used for planning, resource assessment, or land-management decisions.

SVM exhibited the most consistent performance across the evaluation measures. Its 83.3% overall accuracy, 81.7% balanced accuracy, 88.5% sensitivity, 85.2% precision, 75.0% specificity, and MCC of 0.643 indicate that it combined effective agricultural-land detection with stronger exclusion of non-agricultural observations than the alternative classifiers. RF produced moderate performance, while ANN and CNN demonstrated comparatively high sensitivity but lower specificity. The neural-network models therefore detected agricultural locations effectively but were more susceptible to false-positive classifications, which corresponded with their larger estimates of agricultural extent.

The CNN result is particularly informative because the model did not outperform the conventional machine-learning algorithms despite its capacity for hierarchical spatial feature extraction. The finding demonstrates that algorithmic sophistication alone is insufficient to guarantee improved agricultural classification. Model performance remains conditional on characteristics of the imagery, training data, landscape, model configuration, and classification objective. Consequently, classifier selection for regional agricultural mapping should be evidence-based rather than determined solely by the perceived sophistication of an algorithm.

Multiple accuracy measures also provided a more informative interpretation than overall accuracy alone. Sensitivity revealed each model's ability to detect agricultural land, while specificity and precision exposed the false-positive tendencies associated particularly with ANN and CNN. Balanced accuracy and MCC further demonstrated the stronger consistency of SVM across the two validation categories. The study therefore establishes that reliable agricultural mapping requires simultaneous consideration of mapped spatial extent and classifier error structure.

4.2 Recommendations

Future agricultural mapping in Anambra State should prioritise classifiers demonstrated to provide an appropriate balance between agricultural detection and non-agricultural discrimination. SVM should therefore be considered a suitable baseline algorithm for comparable regional applications, although its performance should be independently validated whenever imagery, seasons, training samples, or study areas change.

Future studies should expand the quantity and spatial distribution of independent reference observations, particularly around agricultural-forest boundaries, fallow areas, fragmented farms, and peri-urban agricultural zones where spectral confusion is likely

to occur. Probability-based validation sampling should also be considered because rigorous sampling and response designs strengthen both accuracy assessment and area estimation (Olofsson et al., 2014).

Agricultural area should not be estimated solely from raw classified pixel counts when precise land-area statistics are required. Reference-sample-based error adjustment and uncertainty estimates should accompany mapped agricultural areas because classification errors can produce discrepancies between mapped and actual class extent (Olofsson et al., 2014).

Multi-temporal satellite observations should further be investigated to capture crop phenology and distinguish actively cultivated land from fallow vegetation, forest margins, and other spectrally similar surfaces. Such temporal information may improve discrimination within heterogeneous African agricultural landscapes where fragmented fields and complex crop cycles present persistent mapping challenges (Xiong et al., 2017).

Future comparative experiments should optimise RF, SVM, ANN, and CNN hyperparameters systematically and document training configurations to establish whether observed differences arise from fundamental classifier behaviour or parameter selection. Neural-network approaches should particularly be evaluated with larger training datasets and alternative architectures before conclusions are generalised beyond the conditions investigated here. Finally, future research could extend the binary agricultural-land assessment towards crop-type classification, enabling remote sensing to support more detailed agricultural inventories, crop monitoring, food-security assessment, and evidence-based agricultural planning in Anambra State.

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