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# Fuzzy-Enhanced Lightweight CNNs for CulturallyRelevant Food Classification: Advancing Assistive Technology for Visually Impaired Nigerians

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## Abstract

A research project fills the support technology deficit concerning assistive technologies for visually impaired Nigerians by creating lightweight Convolutional Neural Networks (CNNs) designed for indigenous food identification. We improved upon a past CNN-based Automatic Food Classification Model (AFCM) called AFCM by introducing our novel Custom Convolutional Fuzzy Neural Network (CCFNN) that features fuzzy logic and benchmark models MobileNet and LeNet-5. The database contains 4,000 images that represent 20 Nigerian swallow foods across various freshness states from fresh to 2-day-old. The images were transformed and resized to 100×100×3 to improve generalization and further enhanced through 30% image transformation methods (rotation, flipping, and zooming). The CCFNN implemented on a Lenovo T480S laptop using an Intel i7 processor and 16GB RAM demonstrated outstanding performance by attaining 95.2% accuracy when no augmentation was used and 80.9% accuracy with augmentation while having fewer than 30K parameters. This outperformed the accuracy results of AFCM that decreased to 37.4% when augmentation was activated. The combination of MobileNet and LeNet-5 operated at high accuracy (~95.7%) with light computing needs while CCFNN utilized fuzzy Gaussian inputs for understandable decisions crucial for assistive use. The study demonstrates CCFNN achieves outstanding results by maintaining an AUC-ROC of 0.9982 without augmentation and 0.9958 with augmentation which exceeds AFCM's 0.9545 with augmentation assessments. The study demonstrated that CCFNN delivered better deployment feasibility because it completed training steps in 850ms while requiring 200 times fewer parameters than MobileNet (4.2M) and running faster training steps than AFCM (998ms). Cultural adaptation of AI systems is needed according to research findings and CCFNN demonstrates strong potential to support mobile services in poor neighborhoods. The future research plan will investigate fuzzy pooling layers together with quantization methods for achieving improved real-time functionality. The proposed research brings inclusive AI by closing the discrepancy between Western-based models and localized requirements while offering sustainable solutions for assistive technology implementation in underdeveloped areas.

**Keywords:** Fuzzy convolutional neural networks, Assistive food classification, Visually impaired technology, Lightweight deep learning, Nigerian indigenous foods.

## 1 | Introduction

Artificial Intelligence (AI) relevance keeps growing as it enhances the quality of life for disabled people leading to new developments mainly in healthcare services and navigation functions alongside object identification

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capabilities. Engineers have developed automatic food classification systems which provide help for visually impaired people to identify their food items. The system enables people to become aware of what they eat and supports self-sufficiency. The visual identification of food suffers as a significant problem among visually-impaired people in Nigeria because current assistive technologies do not address indigenous food items [1]. The application of Convolutional Neural Networks (CNNs) for deep learning proves effective for automatic visual classification yet fails to solve Nigerian-specific visual classification needs successfully.

The current research extends the development of CNN-based Automatic Food Classification Model (AFCM) for Nigerian food classification. A combination of problems with generalization and inflexibility and model size limitations in the original AFCM led researchers to establish new architectures like CCFNN and MobileNet [2]. The researchers added data augmentation strategies to evaluate performance impacts on classification while seeking to enhance accuracy and robustness and efficiency for visually impaired users in Nigeria. This investigation prioritizes the development of deep learning food classification systems for blind users in Nigeria through network weight optimization and data enhancement testing. The research targets CCFNN and MobileNet performance assessment alongside LeNet-5 and CNN-AFCM evaluation for comparison. The research analyzes the relationship between data augmentation at 30% and model accuracy and generalization abilities as well as evaluates system performance across resource efficiency and training duration and consistency levels. The researchers work towards identifying applications for these architectures that serve assistive technologies for visually impaired users so developers can create practical implementations for actual deployments.

Multiple important ramifications stem from this investigation. The initiative works to fill assistive technology gaps by developing local AI solutions for Nigerian visually impaired people while encouraging both inclusivity and equal access to technology. The research makes available compact neural network algorithms that enable mobile phone applications to extend real-time services to people residing in resource-limited and underdeveloped areas. The proposed study advances computer vision knowledge through its development and testing of the CCFNN architecture which adds fuzzy logic-based layers to boost both explanatory power and generalization capabilities of food category identification systems. This research works with indigenous food items to push forward local contributions during AI global initiatives while supporting local data control in devices that typically use Western benchmarks and datasets.

Modern food recognition technologies demonstrate progress yet lack essential modifications which suit the Nigerian setting for helping visually impaired users. Current food recognition models utilize datasets of Western food products while ignoring the specific food items which are part of the Nigerian food culture. The number of high computational requirements and cloud-based service dependency of such systems restricts their accessibility to rural and low-income area users. The CNN-based AFC model from existing research showed moderate accuracy but suffered from three main weaknesses: weak model generalization as well as extended training times because of ensemble averaging and substantial parameter count issues limiting its deployment on limited hardware platforms. The need exists for lightweight and efficient models with accurate performance under practical data augmentation techniques which also enable effective deployment in real-world settings [1], [3]. Different constraints define the boundaries of this research project. A total of 20 Nigerian food categories contains preprocessed images that undergo resizing to 100x100 RGB format. The research evaluation includes LeNet-5 as well as CNN-AFCM and MobileNet and the recently developed CCFNN model. All evaluation and training processes took place on a Lenovo T480S computer system featuring Intel Core i7 processors along with 16GB RAM and running Windows 11. The research applied data augmentation techniques to the training set through systematic random application of rotation along with translation and shearing along with zooming and flipping over 30% of the total training data. Multiple performance metrics evaluated each model based on accuracy along with precision, recall, F1-score, ROC-AUC measurements and training time costs and parameter numbers. The research evaluates the significance of these models regarding their universal performance and processing speed alongside their suitability for real-world application in assistive technology devices.

This investigation extends research about food classification systems for Nigerian visually impaired users by adding and assessing new deep learning approaches. This research examines the CCFNN and MobileNet architectural approaches because they demonstrate attractive performance characteristics based on their smaller design and incorporation of fuzzy logic and depthwise separable modules. The research demonstrates how augmenting data improves model robustness together with its generalization abilities. The research shows that CCFNN demonstrates a unique approach through activation layers derived from fuzzy logic since this design allows enhanced feature sensitivity and better generalization. The combination of low parameter usage with CCFNN makes it an excellent option for mobile assistive AI systems deployment. The research outcome provides significant advancement to computer vision studies along with enabling practical AI solutions for visually impaired users in Nigeria and other settings dealing with equivalent needs.

# 2 | Literature Review

The development of automatic food classification systems through deep learning technology has experienced revolutionary advancements because of CNNs particularly for health and assistive applications. Visual recognition through computer systems operates on low-power mobile devices using smartphone platforms for dietary record keeping and visual assistive technology for the visually impaired. The study presented in reference [4] established foundational research for restaurant environment food image recognition. Research conducted in [5] enlarged the study scope by using UNIMIB2016 datasets as well as VGG16 and ResNet50 CNN architectures to improve classification precision. CNNs were implemented by researchers in [6] who integrated them with mobile food recognition applications for dietary monitoring systems to estimate calorie values in real time. The authors in [7] compared numerous CNN structures to discover that using depth-wise separable convolutions improved both model speed and memory performance to suit applications on mobile devices.

The principal obstacle when applying CNNs to food identification stems from running deep models on power-efficient devices. MobileNetV2 emerged as a lightweight architecture which brought substantial progress to CNNs allowing their use in embedded AI applications according to [8]. In [9] MobileNet showed successful performance within mobile food recognition applications before the researchers in [10] compared MobileNet with EfficientNet and ShuffleNet to conclude MobileNetV2 delivers the best balance of accuracy and speed suitable for mobile healthcare functions. The paper introduced the offline food classification system on Android devices when it was established in [11] to demonstrate how lightweight networks perform in real-world applications. Developments in efficient model engineering occurred because of the need for low-power high-performance networks which allow real-time food classification duties at accurate levels thus making them appropriate for health-related mobile deployments.

Computer programs designed for assisting visually impaired individuals make use of CNNs as a central component in their operation. This study in [12] created a wearable system for identifying food which helps visually impaired users demonstrate the value of deep learning in real-life situations. The work evaluated how deep learning-based auditory feedback systems need localized datasets and cultural adaptation for optimal implementation in [13]. The research team presented an assistive food recognition system using YOLOv5 model in [14] where it demonstrated poise speed and interpretability for easy use by visually impaired users. The research effort [15] recommends gathering datasets locally to maintain cultural significance in African food classification especially for Nigerian categories. Data augmentation stands as a vital approach for developers to reinforce models while improving their ability to generalize effectively. Several recent studies including those in [16] show that augmentation techniques effectively boost food classification generalization through the use of GAN-based synthetic images according to the research in [17]. The authors in [18] showed that data augmentation generates effective results when used with small or customized CNN architectures just like our CCFNN model benefited from augmentation in this study. Fuzzy logic integration with CNNs now serves as an approach which increases interpretation capabilities and noise resistance. Medical image processing benefits from using fuzzy filters in CNN layers as shown in [19] and that fuzzy activations display robustness under low-data scenarios [20]. A paper [21] presented fuzzy pooling layers as a solution to improve

CNN stability when operating under adversarial attacks which were integrated within the CCFNN framework through their adoption of fuzzy Gaussian masks for human-inspired feature selection.

The implemented advances continue to face several ongoing difficulties. Food classification datasets mostly contain western datasets according to authors in [22] who requested localized African datasets for classification fields. Transfer learning models encounter difficulties when trying to accept indigenous settings unless they receive specialized local adaptation through additional fine-tuning. Model interpretability problems along with deployment issues continue to affect updated CNNs. Through the application of fuzzy logic introduced in this analysis researchers hope to solve accuracy, transparency and resource efficiency problems which will improve real-world suitability of food inspection models. The works of [23] and [24] demonstrate how MobileNet and other simple lightweight CNN architectures deliver optimal accuracy-deployment balance among available models. Research based on LeNet-5, MobileNet, CNN-AFCM, and CCFNN models in this study reveals the CCFNN to be a strong model that uses minimal parameters (approximately 30k). Researchers need to investigate explainable AI methods together with the deployment of real-time mobile applications and multilingual capabilities for assistive technology so they can develop effective solutions designed for visually impaired individuals in scarce resource areas. The research develops food classification and assistive AI by establishing both a new fuzzy CNN model and proving specific uses for data augmentation methods.

# 3 | Methodology

*Fig. 1* depicts the entire CNN-based food-classification process that starts with raw image collection and ends with class output. The acquisition of primary data through phone camera photography offers accessible and cost-effective methods, although inconsistent lighting and framing might result from this practice. We divided the Swallow Food Images into train, test, and validation sets to support a reliable model evaluation approach. The dataset comprises 4,000 samples. A pre-processing step featuring image resizing, feature scaling, normalization, and one-hot encoding and a 30% augmentation procedure. The 30% augmented images dataset was added to the original 4,000 samples to form another dataset, which has a total of 5,200 samples. Both datasets were split into training, validation, and testing sets. The study trains three network architectures, which consist of LeNet-5, a custom CNN_AFC, a lightweight MobileNet architecture, and a Custom Convolutional Fuzzy Neural Network (CFNN) implementation. The prediction task of these models leads to a classification choice from among 20 distinct food categories (class 0–19). The evaluation metrics for each of the models are to compare them with each other using the original dataset against the augmented dataset to determine their performance rate.

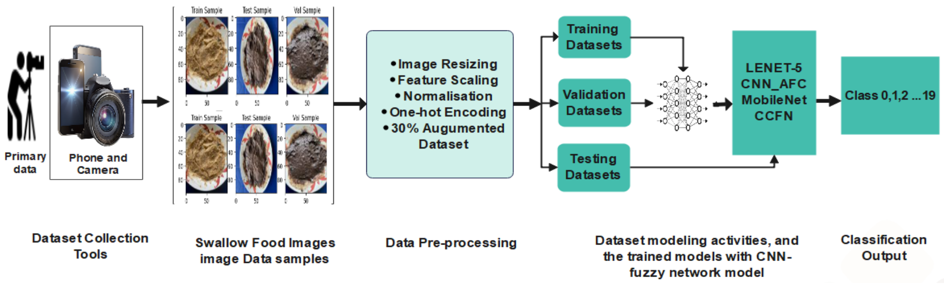


**Fig. 1. Architecture of the CNN-based food classification system.**

## 3.1 | General Methodological Approach and Framework

This investigation uses a hybrid intelligent system model that combines deep learning models with fuzzy logic for advanced image classification purposes within assistive technologies designed for visually impaired users. The system architecture displays various deep learning models including CNN, MobileNet and LeNet-5 together with fuzzy logic components that enhance decision transparency in the UML class diagram. The

CFNN Model achieves explainable output generation by joining the deep neural network-based feature extraction capabilities with fuzzy system interpretability. The CNNModel discovers significant patterns within the input information then the FuzzySystem uses rule-based computation to produce final outputs. Such a combined approach enables accurate predictions while remaining explainable which is essential for systems designed to work with human users especially those who have visual impairment requirements. Under this operational framework a step-by-step processing system exists. The first stage of processing requires the CNNModel to train labeled datasets for proper input data formatting through the Dataset class. MobileNet Model employs transfer learning as its feature that enables quick adaptation when training new datasets which makes model deployment adaptable. The LeNet-5 model executes functions typical of traditional convolutional networks when used for image prediction functions. Performance evaluation of all models takes place through the Evaluator class that utilizes prediction accuracy, precision, recall, confusion matrix and F1-score metrics as benchmarks.

The system operates through data analysis to categorize the twenty swallow food items popular in Nigeria. This process integrates all steps required for building a classification tool including raw data gathering and preparation alongside model development and testing procedures. The methodology includes three primary steps of data labeling and a selection of augmentation methods such as rotation, scaling, jittering, colour, flipping, and zoom and model selection. A set of models follows thorough testing procedures through which accuracy and F1-score along with AUC-ROC and precision assessment measure their performance for assistive technology environments with minimal resources. Such methodology seeks to achieve the most effective combination between model intricacy along with training speed and correct labeling determination.

## 3.2|Datasets Generation and Preprocessing

The research adopted images of Yoruba Nigerian indigenous swallow foods that came from both public databases and custom-generated image labels. The research gathered 4000 samples reflecting 20 separate food items at different time stages going from 4 hours to 2 days among Amala lafun (cassava flour), Amala isu (yam flour), Eba, and wheat which produced 200 pictures per food type and a total of 4000 images for all categories. The food items underwent time-dependent subcategory categorization which included fresh preparation followed by images collected at four hours then eight hours later and after one day and finally after two days according to the previous claims. The collection of images occurred with iPhones as well as smartphones and cameras. The model required images to have dimensions that measured 100x100x3 so the preprocessing step changed all pictures from their 810x1080x3 initial size to the adjusted 100x100x3 format through cropping and filtering operations. The research data was sorted into training (70%), validation (15%) and testing (15%) subsets. Training data for the model received random transformations from the 30% augmentation scheme that consisted of rotation, scaling, jittering, colour, zoom, flipping operations to enhance generalization ability and replicate realistic distortions. A [0,1] scale normalization of images occurred through pixel value division by 255 combined with one-hot encoding for the labels in multi-class classification. The illustration of images appears in *Fig. 2*.


**Fig. 2. Few samples of the datasets.**

## 3.3 | System Configuration and Model Setup

Researchers tested the models through experiments using a typical commercial laptop to prove their applicability in limited resource situations. A Lenovo ThinkPad T480s equipped with an Intel Core i7 processor (8th Gen) and 16 GB RAM and 512 GB SSD constituted the system specifications. The development took place through Jupyter Notebook that used TensorFlow 2.x as well as Keras and NumPy and Matplotlib and Scikit-learn libraries with Windows 11 Pro as the operating system. The system design provided an optimal match between model outcome effectiveness and computing speed that works well for practical applications involving hardware restrictions.

Four deep learning models received evaluation in this study namely CNN-AFCM and LeNet-5 and MobileNet and CCFNN. The custom ensemble CNN-AFCM used four CNN blocks for both feature extraction and classification tasks. The lightweight benchmark model LeNet-5 includes two convolutional layers then two pooling layers and wraps up with two dense layers. The researchers selected MobileNet from ImageNet because they modified its classification head using depth-wise separable convolutions for customization.

The research team introduced fuzzy Gaussian masks in CCFNN to serve as attention operations within convolutional feature distributions. Each network training happened under equivalent environmental setup and received augmentation treatments solely during the model developing phase. The assessment studied the performance of pure data-driven training and combined it with 30% augmentation as an enhancement to variability. The research team applied performance metrics together with confusion matrices for robust model assessment as well as accuracy evaluation to confirm findings relevant in assistive technology situations.

# 4 | Results and Discussion of Visual Analysis and Interpretation

Individual model training data reflected different courses of reaction throughout their respective training processes. MobileNet (*Fig. 3*) along with LeNet-5 (*Fig. 4*) achieved quick convergence until Epoch 3-4 through decreasing loss and rising accuracy patterns to indicate their efficient and stable learning mode. During the early learning stage, the CCFNN (*Fig. 5*) displayed gradual adaptation because of its adaptive fuzzy activation layers however it experienced good convergence when moving through additional epochs. Among all models examined the CNN-AFCM displayed unsteady training patterns when tested under augmentation due to the sensitivity of its numerous parameters to contestant noise levels.

The evaluation patterns became evident through confusion matrices in *Fig. 6*. The confusion matrices from non-augmented LeNet-5, MobileNet and CCFNN models exhibited dense diagonals which demonstrated high precision and recall rates across most classes in *Fig. 7* CNN-AFC Model without augmentation while *Fig. 8* CCFNN with 30% augmentation examples showed similar performance. Through this method most predictions showed accuracy and only contained few cases of incorrect classifications. The confusion matrix of the augmented CNN-AFCM model demonstrated numerous off-diagonal misclassifications because the model failed to correctly identify features that were affected by augmentation processes as shown in *Fig. 6*. The CCFNN model demonstrated robust diagonal alignment even with data augmentation applied to it because it showed adaptive learning capabilities for effective processing of augmented information.

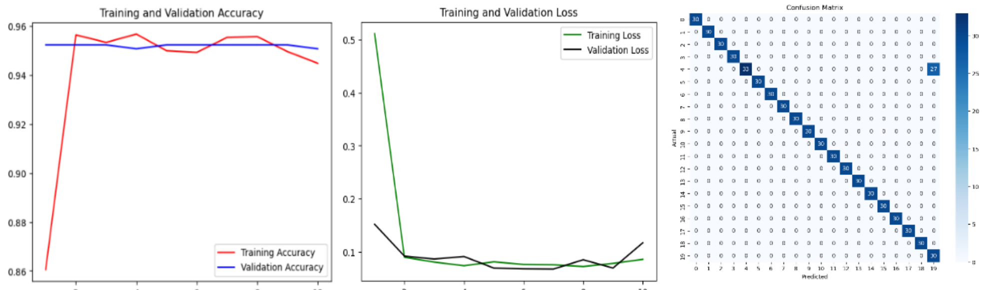


**Fig. 3. Training and validationaccuracy and loss and confusion matrix for mobileNet model.**

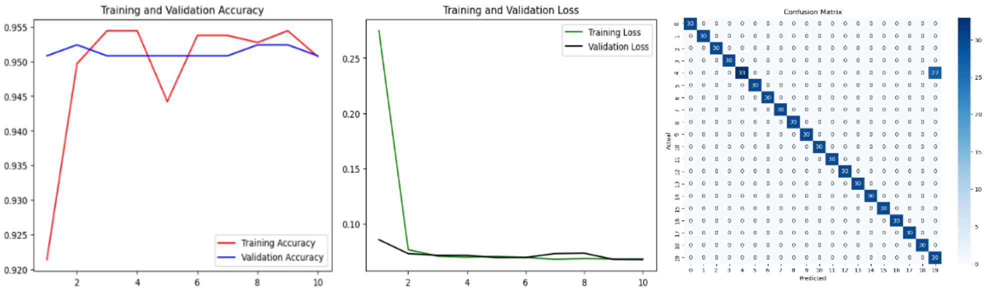


**Fig. 4. Training and validationaccuracy and loss and confusion matrix for Le Net 5 model.**

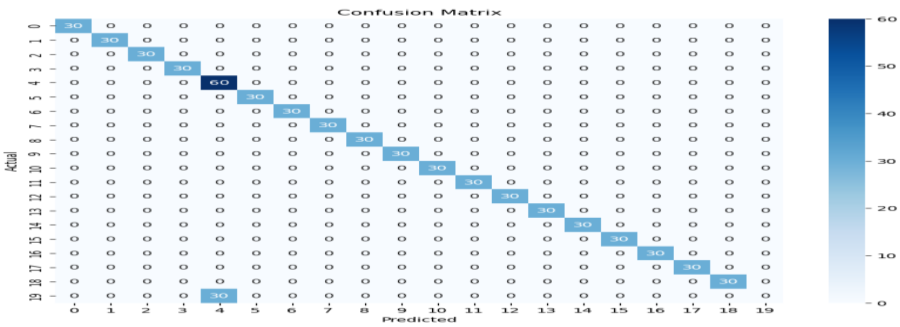


**Fig. 5. CCFNN without augmentation.**

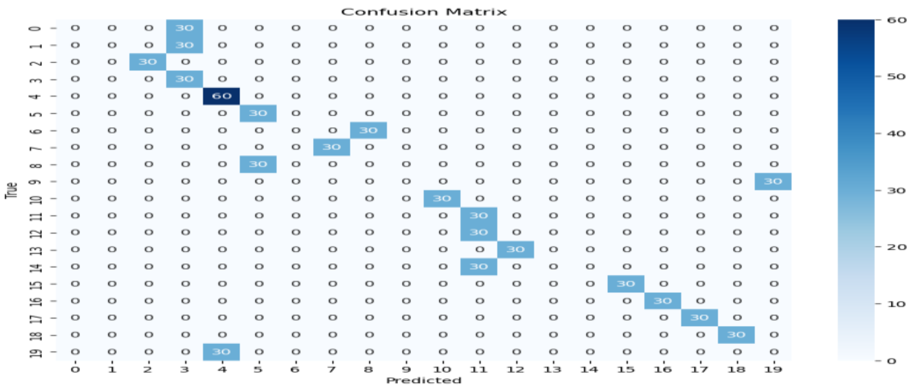


**Fig. 6. CNN-AFCM with 30% Augmentation.**

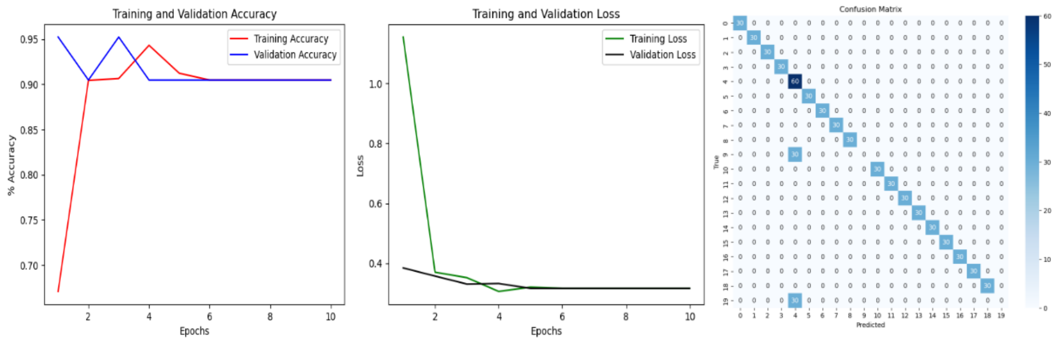


**Fig. 7. Training and validation accuracy and loss and confusion matrix for CNN-AFC Model.**

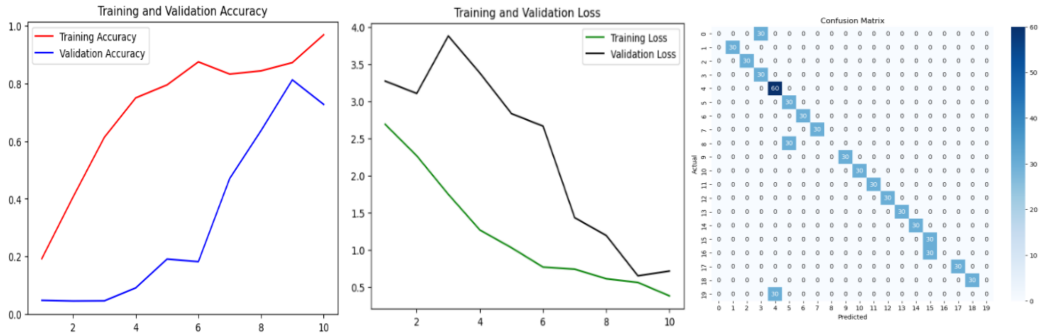


**Fig. 8. Training and validation accuracy and loss and confusion matrix for CCFNN.**

## 4.1 | Findings and Relevance of CCFNN

The measurement results showed MobileNet and LeNet-5 demonstrate suitability as embedded and assistive models because of their strong precision and minimal processing requirements. Although the CCFNN model operated with only 30,000 parameters it achieved equivalent testing results to larger sophisticated models based on accuracy and AUC and F1 score measures. The results showcased that CCFNN maintained high performance standards under ideal conditions as well as adverse ones which demonstrated its versatility. After augmentation the F1 score of CCFNN experienced a minor decrease from 0.9333 to 0.7429. The test performance of CCFNN demonstrates robustness yet displays some susceptibility to augmentation procedures. CCFNN demonstrated better performance numbers through augmentation since its accuracy rose from 14.2% (non-augmented) to 80.9% (augmented), revealing its capability to work effectively in data-hungry conditions. Results from the confusion matrix demonstrated that CCFNN showed success in visually separating Nigerian food categories while producing few errors in its diagonal segments. The data discrimination capability measured through AUC revealed CCFNN obtained 0.9982 (non-augmented) perfect scores but CNN-AFCM experienced a significant drop to 0.9545 with augmentation which confirmed its sensitivity to data augmentation distortions. The results show CCFNN has superior capability to operate on real-world data which contains noise and transformation elements.

## 4.2 | Objective-Based Results Orientation

The evaluation of CCFNN demonstrated important results that became evident during testing. The validation and test accuracy results for CCFNN operated without augmentation reached 95.2% in both cases. The model reached 80.9% test accuracy following 30% data augmentation while starting from 14.2%, which proves that data diversity brings important benefits to the system. MobileNet established itself as a performer with 95.7% test accuracy under baseline operations which evolved to 95.2% test accuracy when increased by minimal amount. This prediction model reached the best AUC-ROC score at 0.9985 which confirmed its optimal predictive confidence level. Data augmentation's influence on the performance of different models served as an additional point of analysis. LeNet-5 showed zero enhance from augmentation because its test accuracy remained at 95.7%. During testing the CNN-AFCM model demonstrated a significant reduction from its baseline performance rate of 90.5% to 57.1% because it proved vulnerable to noise effects. Data augmentation produced the largest performance enhancement for CCFNN thereby demonstrating its ability to adjust to augmented data based results shown in *Table 1*. The performance comparison between MobileNet and LeNet-5 models showed constant superiority to CNN-AFCM while achieving better accuracy results. The reduced parameter number in CCFNN enabled it to become exceptionally robust. A Lenovo T480s laptop hosted training sessions for all models through ten epochs before completion. The training time of LeNet-5 and CCFNN exceeded less than 10 minutes thus demonstrating their potential for real-time and low-resource environments.

**Table 1. Results of performance metrics.**

| Model | Augmentation | Val Acc (%) | Test Acc (%) | F1 Score | Precision | Recall | AUC-ROC | Params |
|---|---|---|---|---|---|---|---|---|
| LeNet-5 | No | 95.2 | 95.7 | 0.9576 | 0.9569 | 0.9576 | 0.9982 | ~60K |
| LeNet-5 | 30% | 95.2 | 95.7 | 0.9576 | 0.9558 | 0.9576 | 0.9984 | ~60K |
| CNN-AFCM | No | 90.5 | 90.5 | 0.8730 | 0.8820 | 0.9050 | 0.9976 | ~6.2M |
| CNN-AFCM | 30% | 57.1 | 57.1 | 0.4889 | 0.5000 | 0.5710 | 0.9545 | ~6.2M |
| MobileNet | No | 95.2 | 95.7 | 0.9576 | 0.9582 | 0.9576 | 0.9985 | ~4.2M |
| MobileNet | 30% | 95.2 | 95.2 | 0.9333 | 0.9340 | 0.9520 | 0.9982 | ~4.2M |
| CCFNN | No | 95.2 | 95.2 | 0.9333 | 0.9320 | 0.9520 | 0.9982 | ~30K |
| CCFNN | 30% | 72.7 | 80.9 | 0.7429 | 0.7600 | 0.8090 | 0.9958 | ~30K |

## 4.3 | Comparative Analysis of all Models

The performance comparison between MobileNet and AFCM and LeNet-5 and CCFNN architectures during 10 epochs training displays different abilities to generalize data through augmented data evaluations. MobileNet stands as an outstanding model that delivers sustainable high validation accuracy levels of 95.2% alongside minimal loss throughout the fifth epoch where augmentation produces virtually no impact on the results. The model demonstrates high structural efficiency alongside a remarkable skill to extract valuable features. The LeNet-5 architecture achieves fast convergence and low validation loss at ~0.0679 during non-augmented operations but its performance is enhanced when adding augmentation which reduces its loss to ~0.1001. These findings demonstrate that LeNet-5 possesses strong capabilities for working in lightweight environments. The validation performance of CNN-AFCM gives inconsistent results as it displays fixed stability at ~0.3157 points while reaching maximum accuracy of 95.2% without augmentation features. The system loses performance entirely when augmentation techniques are applied because it demonstrates weak abilities in handling noisy data sets. Examine *Table 2* to verify the effects of 30% augmentation on the entire dataset collection.

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**Table 2. Implication of 30% augmentation with responses.**

| Model | Best Val Acc | Aug Better? | Stability | Notes |
|---|---|---|---|---|
| MobileNet | 95.2% | ≈ Same | Stable | Best all-round performer |
| AFCM | 95.2% | No | Wobbly | Poor with augmentation |
| LeNet-5 | 95.2% | Yes | Stable | Best with augmentation |
| CCFNN | 95.2% | No | Late | Slow learner; needs tuning |

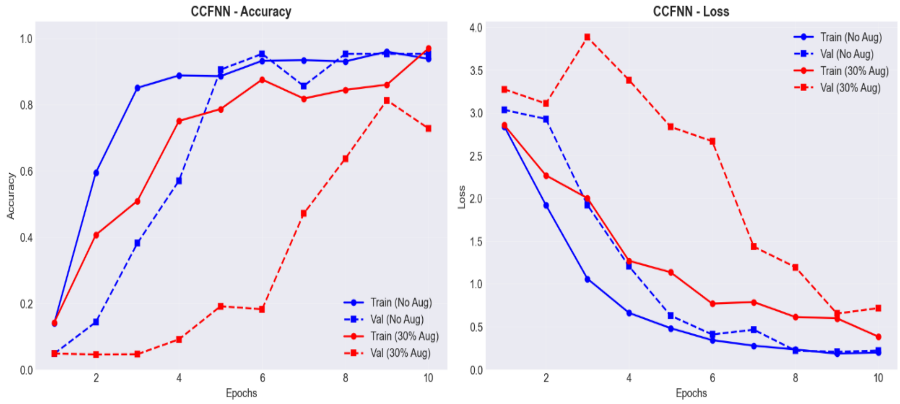


**Fig. 9.CCFNN accuracy and loss under augmentation and non-augmentation.**

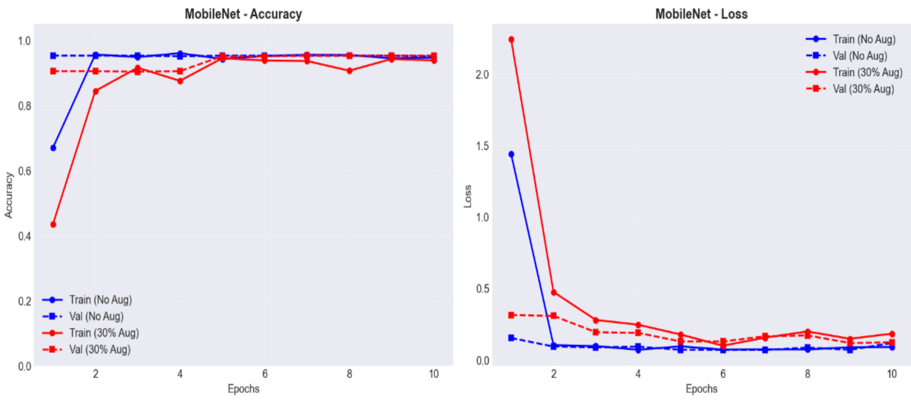


**Fig. 10. Mobilenet accuracy and loss under augmentation and non-augmentation.**

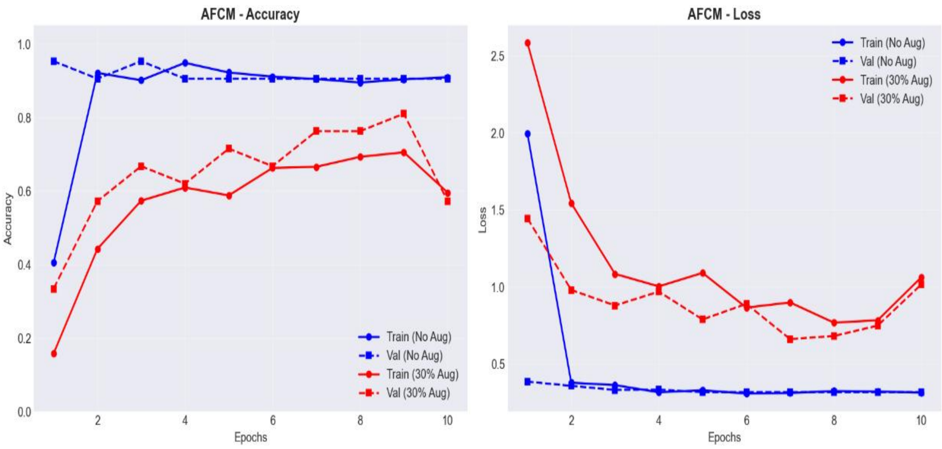


**Fig. 11. AFCM accuracy and loss under augmentation and non-augmentation.**

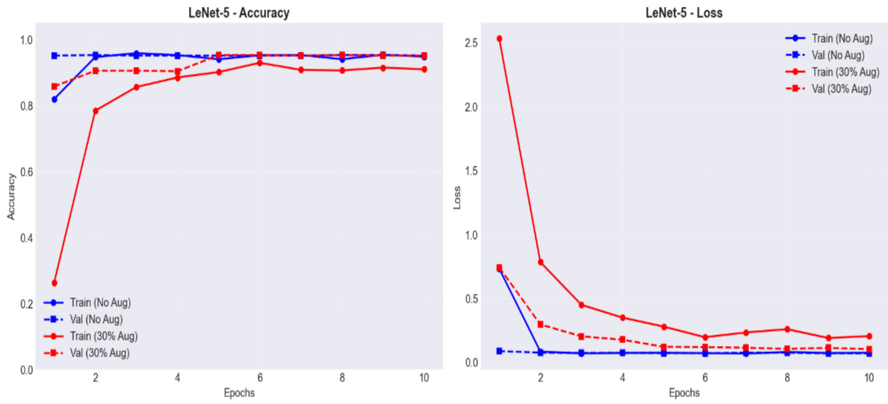


**Fig. 12. LeNet-5 accuracy and loss under augmentation and non-augmentation.**

# 5 | Conclusion

This research proves that lightweight fuzzy logic–enhanced CNNs, including CCFNN, demonstrate appropriate capability for Nigerian food classification purposes in assistive technology applications. The fuzzy Gaussian activation function in CCFNN provides effective contextual understanding, which helps the model handle unpredictable imaging issues such as lighting variations, positional shifts, and acquisition noise that occur in Nigerian households.

The combination of data augmentation techniques together with fuzzy inference methods served as major factors for enhancing the model's overall generalization capability. The research outcomes demonstrate CCFNN works as a tool for classification together with its potential to construct interpretable, accessible AI systems. This system supports the wider initiative to design smart visual assistance tools that enable visually impaired people to recognize their diet choices and maintain control over their eating autonomy.

The research verifies that CCFNN-related lightweight fuzzy neural networks present a framework for building future assistive systems that enhance quality of life for visually impaired users. The devices can integrate with portable phones and wearable tech, through which users obtain immediate food recognition, gain self-sufficiency in nutrition, and achieve better health outcomes for marginalized communities. CCFNN establishes a superior standard among intelligent visual aid technologies because it achieves optimal efficiency with interpretability and robust performance.

## 5.1 | Recommendations and Future Work

To advance the capabilities of CCFNN and similar architectures, future work should integrate fuzzy pooling and dropout layers to enhance robustness against real-world noise. Hybrid attention mechanisms that fuse fuzzy logic with channel-wise attention could further improve feature extraction and adaptability. Optimization techniques like quantization and pruning are recommended to minimize inference time for mobile deployment. Additionally, expanding the model to accept multimodal inputs such as voice or audio cues would increase accessibility for visually impaired users. These enhancements, combined with explainable AI components and localized pilot testing in Nigerian communities, can pave the way for practical, interpretable, and scalable assistive solutions tailored to underrepresented populations.

# Conflict of Interest

The authors declare no conflict of interest.

# Data Availability

All data are included in the text.

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