ISSN: 4120 – 5671
Volume 12, Number 1, 2026
Advanced Journal of Physical Science Research

DETECTION SYSTEM FOR UNDER-AGE VOTERS USING CONVOLUTIONAL NEURAL NETWORK (CNN) AND IRIS DATA

Ohia Obi[1], Asagba P.O.[2], Onuodu F.E.[3]
Department of Computer Science
University of Port Harcourt, Choba, Rivers State, Nigeria.
opwservices@gmail.com[1]

Abstract
Underage voting continues to weaken the credibility of elections in Nigeria, even after the introduction of the Bimodal Voter Accreditation System (BVAS), because voter-age verification still depends on declared age, documents, and manual checks that can be falsified or pressured. This paper presents a detection system for underage voters that classifies iris images into two classes, adult (18 years and above) and under 18, using a Convolutional Neural Network (CNN). An integrated methodology comprising experimental research, a machine learning pipeline, and the Object-Oriented Analysis and Design Method (OOADM) was adopted. Iris images drawn from the CASIA, MMU, and Kaggle repositories (10,000 images; 70:10:20 training, validation, and testing split) were segmented, normalized with Daugman's rubber sheet model, and passed to an AlexNet-based CNN with batch normalization, dropout, and a two-neuron Softmax output, trained for 300 epochs with the Adam optimizer. The model was implemented with Python for the machine learning back end, JavaScript and PHP for the application programming interface (API) at the front end, and MySQL for database management. Performance was evaluated with a confusion matrix and compared with the iris-based age and gender detector of Faluyi et al. The illustrative 300-case evaluation produced 98.33% accuracy, 97.03% precision, 98.00% recall, 97.51% F1-score and a 1.5% false positive rate, against 94.38% accuracy, 96.18% precision, 94.37% recall and a 5.61% false positive rate for the existing system, while processing time fell from 44.23 s to 28.57 s. The results indicate that CNN-based iris analysis can serve as a decision-support layer for voter-age verification, subject to validation in real registration environments.

Keywords: Underage voters; Iris biometrics; Convolutional neural network; AlexNet; Age classification; Electoral integrity; Deep learning

INTRODUCTION

Elections are the most visible expression of democratic governance, and their legitimacy rests on a credible register of voters who are legally entitled to vote. In Nigeria, Section 29(4)(a) of the 1999 Constitution (as amended) defines full age as eighteen years and above [1], and the Electoral Act, 2022 restricts registration and voting accordingly [2]. Even so, underage voting has been reported in successive election cycles. Alphonsus et al. [3] describe underage voting as casting a ballot while below the legal voting age, and observers have documented the practice in the 2015 and 2023 general elections and in state-level polls such as the 2018 Kano local government election [4], [5]. A former Resident Electoral Commissioner in Plateau State disclosed that minors holding valid Permanent Voter's Cards (PVCs) attempted to vote during the February 2023 constituency elections, and several ballots were cancelled [5].

The problem persists because the verification chain is weak at the point of registration. Registration officers, many of them temporary staff, face intimidation from community leaders and political actors who present lists of children for registration, and former INEC commissioners have warned that an inaccurate register undermines electoral transparency [4]. The Bimodal Voter Accreditation System (BVAS) improved accreditation and result transmission, but it authenticates identity through fingerprints and facial images and does not independently estimate whether the person presenting is under 18. Age is therefore still established through declarations, affidavits and certificates that are easy to falsify.

Biometric traits that carry age-related information offer a route out of this difficulty. The human iris is stable, unique to the individual and difficult to forge, and its texture, pupil-to-iris ratio and pigmentation vary measurably with age [6]. Deep learning has made it possible to learn such patterns directly from images. Convolutional Neural Networks (CNNs) are a class of deep networks designed for image analysis; their connectivity pattern is inspired by the organization of the animal visual cortex, and they learn hierarchical features, from edges to complex textures, with minimal manual preprocessing [7]. Earlier age-estimation studies applied CNNs to faces [8], [9] and classical classifiers to fingerprints [10], while the only iris-based

age and gender detector located for this study relied on pre-trained feature extractors with a multi-class Support Vector Machine (SVM) [6].

This paper therefore proposes a detection system for underage voters that couples iris biometrics with an end-to-end CNN. The system accepts an iris image, standardizes it, classifies it as adult or under 18 in near real time, and passes the decision to an application layer backed by a database, so that flagged applicants can be referred for further verification before registration is completed. The rest of the paper is organized as follows: Section 2 reviews related works and identifies the research gap, Section 3 presents the methodology and system design, Section 4 discusses the results, and Section 5 summarizes, concludes and makes recommendations.

Statement of the Problem

Underage voting remains a persistent problem in parts of Northern Nigeria although it is illegal under the Constitution and the Electoral Act, 2022 [1], [2]. Even with the adoption of BVAS, a systemic problem of minors voting remains. It has negatively affected the nation's democracy and, in some cases, invalidated election outcomes, because minors lack the maturity to make voting decisions and can be easily influenced and manipulated by politicians. There is currently no IT-based detection system that estimates a registrant's age from a biometric trait at the point of registration and accreditation. This study addresses the problem by implementing a detection system for underage voters using a CNN and iris data.

Aim and Objectives of the Study

The study aims to develop a detection system for underage voters using a Convolutional Neural Network (CNN) and iris data. The specific objectives are to:

i) design a model for detecting underage voters using experimental design, a machine learning pipeline and the object-oriented design technique;
ii) train the proposed model using a CNN to learn and classify extracted features of iris data, and validate and test the detection system using iris data;
iii) implement the model using Python for the machine learning component at the back end, JavaScript and PHP for the API component at the front end, and MySQL for database management; and
iv) evaluate the performance of the proposed model using a confusion matrix and compare the existing and proposed systems using a comparative analysis approach.

Significance of the Study

The study presents an intelligent model that uses iris biometric data with a CNN to identify underage voters. It offers a new method of verifying voters' ages that improves the integrity, reliability and efficiency of verification and bridges the gap between traditional and modern voter verification systems. It will benefit (i) **electoral institutions** such as INEC, which can adopt the system as a safeguard so that only persons of legal voting age enter the register; (ii) **software and hardware developers**, who obtain a framework for building CNN-based iris authentication systems and a market for iris cameras and related hardware; (iii) **the general public**, since election outcomes will better reflect the will of the people and manipulation through minors will be curtailed; and (iv) **the judiciary**, which will have a tool that reduces the difficulty of establishing age when affidavits and falsified birth certificates are involved and that can reduce litigation over underage voting.

Scope of the Study

The study focuses solely on the use of a CNN and iris data to identify underage voters and on developing a standalone system that is not integrated into any existing electoral database. Testing and validation were carried out with pre-existing iris image datasets obtained from repositories; no real-time biometric data were collected in electoral environments.

LITERATURE REVIEW

Related Works

Ten related studies on biometric and image-based age estimation, iris processing and electoral technology are reviewed, with emphasis on the iris-based work of Faluyi et al. [6]. Table 1 summarises them.

Faluyi et al. [6] developed an iris-based system that detects age and gender in real time. Images of the left and right irises of 190 subjects (1,716 images) were collected, and 570 left-iris images were normalised to 250 × 250 pixels (342 for training and 228 for testing). After segmentation, filtering and normalisation with

Daugman's rubber sheet model, features were extracted with pre-trained deep networks and classified with a multi-class SVM in MATLAB. At a 0.75 threshold, gender prediction reached 95.62% accuracy, 96.55% precision, 92.31% recall and 2.19% false positive rate (FPR), while the best age-group result (20–24 years) was 94.38% accuracy, 96.18% precision, 94.37% recall and 5.61% FPR. **Nwankwo [11]** proposed a predictive model combining a deep CNN, an Ethereum smart contract and the InterPlanetary File System (IPFS) to detect minors attempting to register; the CNN was trained on an age classifier with eight age groups, but the blockchain component could not be tested because of gas-fee limits. **Muhammad et al. [8]** classified adolescence and mature adulthood with a FaceNet-based CNN trained on the All-Age Face dataset, reaching 84.90% training and 85.12% testing accuracy, although the large network caused latency and text on some images degraded matching.

Falohun et al. [10] built a fingerprint-based age and gender detector using DWT with PCA for age classes and a back-propagation network for gender, with 82.14% overall accuracy on 280 fingerprints; no comparison with existing systems was made. **Kennedy et al. [12]** replaced fingerprints with iris templates and a C#-generated PIN for voter registration and authentication, but computational demands caused delays and errors and no neural network was used to handle large image volumes. **Tania and Pooja [13]** implemented iris segmentation with the Hough transform and normalisation with Daugman's rubber sheet model in MATLAB, yet did not capture and process images in real time with an iris device. **Machala et al. [14]** presented a criminal face detection system using Local Binary Patterns Histograms, Fisherfaces and Haar cascades, but reported delays in evaluating the Viola-Jones framework.

Felix et al. [15] introduced DeepUAge, a ResNet50 model trained on the VisAGe dataset of minors' faces, which outperformed other face age classifiers for younger subjects but left a latency problem unresolved. **Angeline and Keerthiga [9]** used CNN-based face recognition for underage driving detection and obtained a high success rate under varied angles and lighting, but supplied no software implementation. **Emmanuel [16]** modelled age fraud in the Nigerian civil service from the dates on educational certificates under the 6-3-3-4 system and built a PHP and MySQL application; the model depends on documents that can be falsified and becomes obsolete if the school system changes.

Table 1. Summary of the related works reviewed

Ref.	Authors (year)	Technique and data	Limitation
[6]	Faluyi et al. (2022)	Iris, deep features + multi-class SVM, MATLAB	Latency; no access control; rigid interface
[11]	Nwankwo (2023)	Face, deep CNN + blockchain/IPFS	Smart contract not tested or deployed
[8]	Muhammad et al. (2021)	Face, FaceNet-based CNN, two age groups	Large network, latency; text on images
[10]	Falohun et al. (2020)	Fingerprint, DWT+PCA, back-propagation	No comparative analysis
[12]	Kennedy et al. (2019)	Iris templates + PIN for voter registration	Delays and errors; no neural network
[13]	Tania and Pooja (2015)	Iris, Hough transform, rubber sheet model	No real-time device capture
[14]	Machala et al. (2023)	Face, LBPH + Fisherface, Haar cascade	Delay in Viola-Jones evaluation
[15]	Felix et al. (2020)	Face, ResNet50 on VisAGe minors dataset	Latency unresolved
[9]	Angeline and Keerthiga (2021)	Face, CNN for underage driving	No software implementation
[16]	Emmanuel (2020)	Certificate dates, PHP and MySQL	Document-dependent; easily falsified

Taken together, the reviewed studies show three patterns. First, face-based CNN approaches [8], [9], [15] achieve useful age estimation but depend on facial appearance, which varies with growth, lighting, expression and, as Nigerian public debate on the 2023 Kano election illustrated, can be disputed by claims that minors merely look younger. Second, fingerprint and document-based methods [10], [16] are easier to deploy but

carry weaker age evidence and are open to falsification. Third, iris-based work [6], [12], [13] benefits from a stable and distinctive trait but has used classical classifiers or identity matching rather than end-to-end deep learning for an eligibility decision.

Research Gap Identified

The study commends the effort of Faluyi et al. [6]. However, the developed iris-based age and gender detection system experienced latency in processing iris data because of anomalies in the datasets, and it was tested on a small sample of 1,716 images. Secondly, it had no framework for identity management through robust user authentication and verification, although personally identifiable information requires access control to prevent identity theft. Thirdly, it featured a rigid graphical user interface that complicated communication between users and the system. Its separate feature extraction and SVM classification stages also under-use the discriminative power of end-to-end deep learning, and it predicted age groups and gender rather than the legal question that matters in elections, whether a person is below 18. This study addresses these gaps by developing a detection system for underage voters using a CNN and iris data.

MATERIALS AND METHODS

Methodology of the Study

An integrated methodology comprising **experimental research**, a **machine learning pipeline** and the **Object-Oriented Analysis and Design Method (OOADM)** was adopted for the analysis, design, development and implementation of the system. Experimental research provided the framework for conducting, controlling and evaluating the experiments; the machine learning pipeline structured acquisition, preprocessing, feature learning, classification and decision-making; and OOADM represented the system as interacting objects, which improves reusability, maintainability and scalability. Key object-oriented features applied include classes, objects, encapsulation, inheritance, polymorphism and abstraction. Unified Modelling Language (UML) diagrams, namely use case, class, sequence, activity and architecture diagrams, describe the structure and behaviour of the system. The machine learning component was built with a CNN trained and validated on an iris image dataset; the application interface was built with PHP and JavaScript and the data were managed with MySQL. Python was chosen for the deep learning model because of its extensive machine learning and image processing libraries. The integrated approach suits a system with several interacting components, namely the user interface, iris acquisition, feature extraction, CNN classification, database management and output.

Analysis of the Existing System

The existing system is the iris-based age and gender detection system of Faluyi et al. [6], developed to establish whether iris features carry enough information to predict age group and gender for identity management. Its dataset comprised the left and right irises of 190 individuals (1,716 images). A subset of 570 left-iris images was resized to 250 × 250 pixels to remove differences caused by lighting, viewing angle, pupil dilation and camera distance. As Fig. 1 shows, the pipeline performs acquisition and segmentation, then splits into geometric feature extraction with correlation on one branch and Daugman normalisation with texture feature extraction on the other; the two feature sets are combined and passed to a multi-class SVM for prediction. Performance was assessed with accuracy, precision, recall and FPR. The system supports broad demographic estimates, whereas election management needs a reliable decision on eligibility (18 and above or under 18).

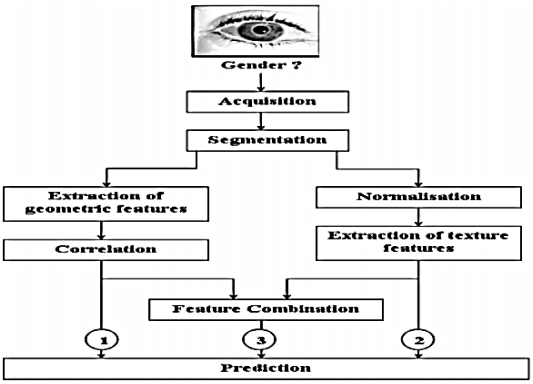


Fig. 1. Architecture of the existing system (source: Faluyi et al. [6]).

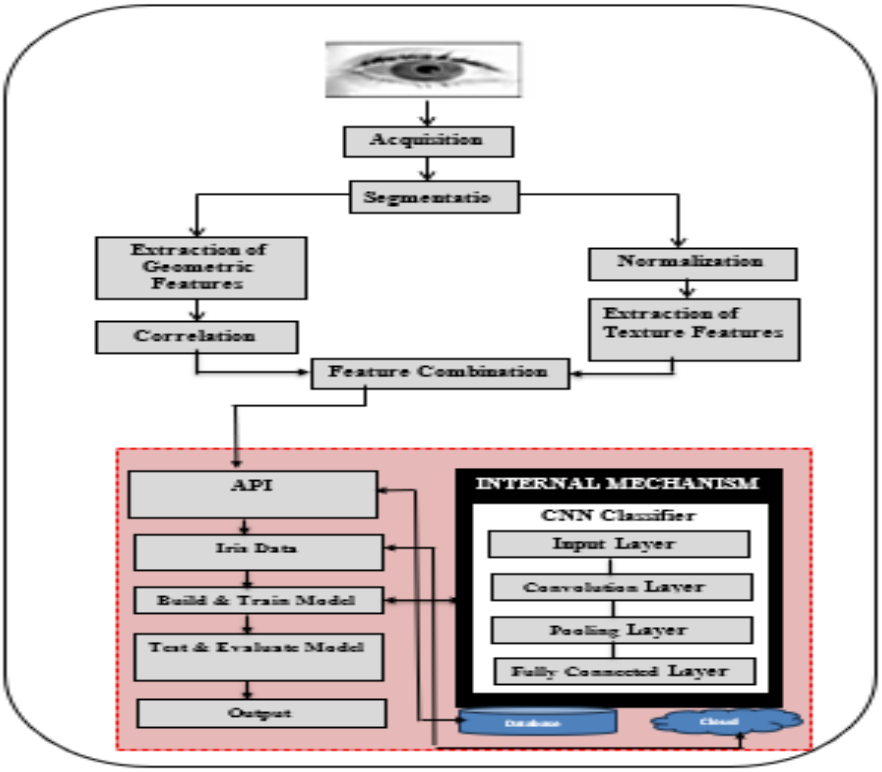
Challenges of the Existing System

The analysis showed the following limitations, which justify the proposed system:

i) **Processing latency.** Noisy or low-quality iris images delay preprocessing and slow segmentation and normalisation.
ii) **Lack of robust identity management.** The framework has no secure user authentication, voter verification, database synchronisation or audit mechanism.
iii) **Rigid user interface.** The interface offers only basic interaction and no flexible administrative functions, which complicates practical deployment.
iv) **Manual feature engineering and conventional classification.** Separate feature extraction and SVM classification add complexity and underuse end-to-end deep learning.
v) **Limited scalability.** The system was tested on a limited dataset, so its behavior on larger databases is uncertain.

Analysis of the Proposed System

The proposed system combines CNN-based iris analysis, image processing, cloud computing, and a relational database to detect underage voters and to improve registration and authentication. Its architecture (Fig. 2) begins with an API that links users to the application through standardized interfaces between the front end, the deep learning model, the cloud services, and the database. Authorized registration officers and administrators register and authenticate users, enroll biometrics and manage voter records, and access controls protect the biometric data. After authentication, officers upload the applicant's iris image and voter information to cloud storage, which acts as a central repository with high availability, scalability, automatic backup, and synchronized records across registration centres.



Stored images are resized, normalized, segmented, contrast enhanced, and denoised to reduce variation in lighting, pupil dilation, and scale. The normalized images feed a CNN, which, unlike conventional methods that rely on hand-engineered descriptors such as PCA, LBP, or Gabor filters, learns hierarchical features and classifies them jointly. After training, the network is tested on unseen iris images and evaluated with a confusion matrix from which accuracy, precision, recall, specificity and F1-score are derived. The classifier is the decision-maker: it labels each applicant as eligible or as a suspected underage voter, and the result is shown to authorized users through the application interface so that flagged cases can be verified before registration. The database stores user, authentication, biometric, prediction, audit, and activity data. Model development, training, and evaluation run on Google Colab with GPU acceleration.

Detailed Analysis of the Proposed System

The CNN Classifier Phase

The CNN classifier is the decision stage of the system. An AlexNet backbone [17] extracts features from preprocessed iris images and classifies applicants end to end, so that ridges, furrows, crypts, pigmentation and collarette texture produce convolutional activation patterns without manual feature design. Fig. 3 shows the classifier and Fig. 4 expands it into the end-to-end machine learning pipeline. Table 2 lists the layer configuration, and Eqs. (1) to (5) give the operations performed.

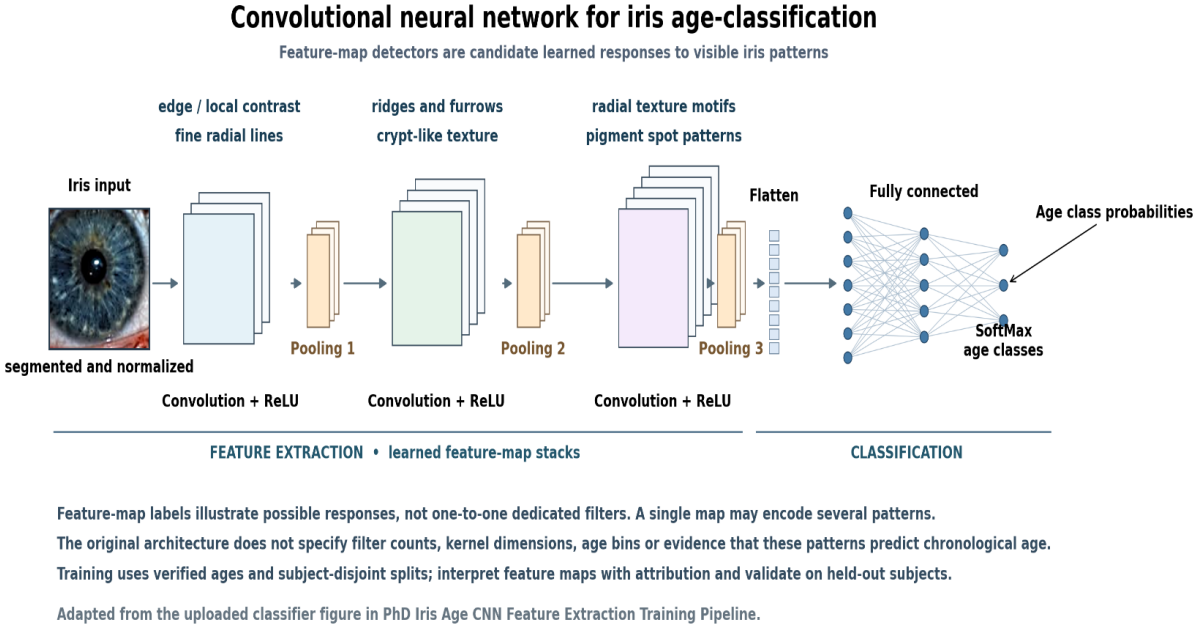


Fig. 3. CNN classifier architecture of the proposed system.

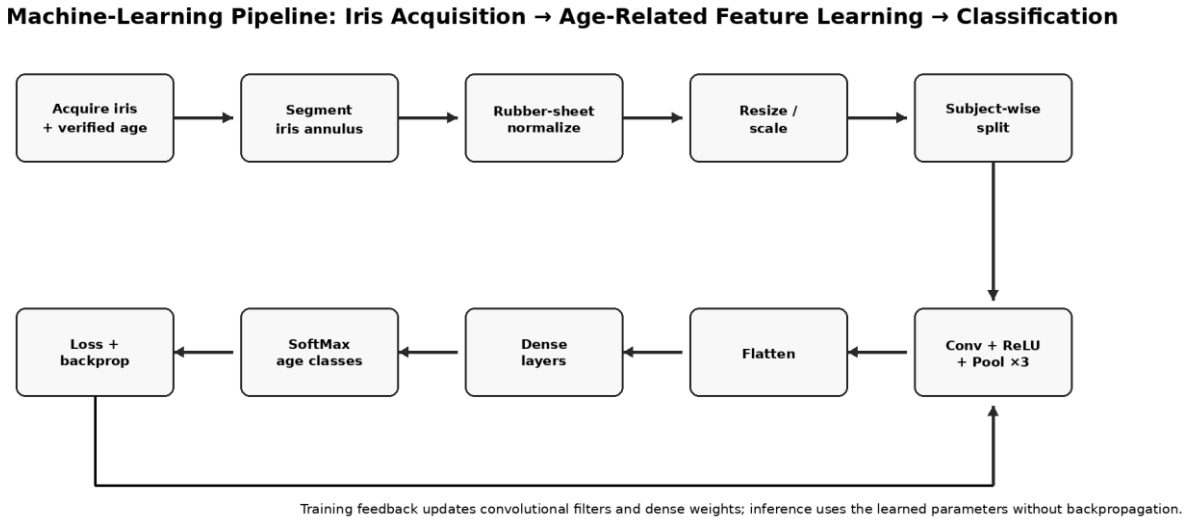


Fig. 4. Expanded end-to-end machine learning pipeline: iris image to age-related feature learning and classification.

Table 2. Layer configuration of the CNN classifier

Layer	Operation	Role in iris age classification
Input	Normalised, segmented iris image	Standardised tensor with pixel values scaled to a common range
Conv2D + ReLU	Learnable filters, Eqs. (1)–(2)	Detect edges, ridges, furrows, crypts and ring structures

Layer	Operation	Role in iris age classification
Batch normalisation [19]	Per-channel mean and variance	Stabilises and speeds up training
MaxPooling2D	2 × 2 window, Eq. (3)	Reduces spatial size and adds shift tolerance
Flatten	7 × 7 × 64 → 3,136 values	Converts feature maps to a vector
Dense (512)	Fully connected, ReLU	Combines features into age-related patterns
Dropout [20]	p = 0.5	Limits over-fitting
Output (2)	Softmax, Eq. (4)	Probabilities for adult and under 18

Each convolutional filter k slides over the input channels c and produces a feature map Z, and the ReLU activation then keeps positive responses:

$$Z_k(i, j) = \Sigma_c \Sigma_m \Sigma_n W_{kc}(m, n) \cdot X_c(i + m, j + n) + b_k \quad (1)$$

$$f(z) = max(0, z) \quad (2)$$

Max pooling keeps the strongest response in each 2 × 2 window, and the Softmax layer converts the two output logits into class probabilities that are compared with the target labels through the categorical cross-entropy loss:

$$y_{i,j} = max_{0 \le m,n<2}\, a_{2i+m,\, 2j+n} \quad (3)$$

$$p_k = exp(z_k) / \Sigma_j\, exp(z_j) \quad (4)$$

$$L = -\Sigma_k\, y_k\, log(p_k) \quad (5)$$

Backpropagation computes the gradients of L and the Adam optimiser [18] updates the weights and biases. For one iris input, an alert is raised when the under-18 probability is not less than a chosen threshold τ; for example, p = [0.269, 0.731] with τ = 0.50 gives a minor alert because 0.731 ≥ 0.50. The software stack comprises Python 3 on Google Colab, TensorFlow and the Keras API, NumPy, OpenCV, Matplotlib and tqdm.

The Dataset Phase

The dataset determines the classifier's accuracy and robustness. Iris images from the CASIA database [21], the Multimedia University (MMU) database [22], and public iris datasets on Kaggle were used for training, validation, and testing. CASIA provides high-resolution infrared images captured under controlled conditions; MMU provides grayscale images (about 320 × 240 pixels) with variation in pupil dilation, eye orientation, and lighting, captured with an LG Iris Access 2200; and Kaggle adds user-contributed collections that increase sample diversity. Fig. 5 shows samples from the three sources and Table 3 summarizes the data. Each image is labelled by verified age (under 18 coded 0, adult coded 1), resized, normalized, denoised and, where needed, augmented. All images of one individual were kept in a single subset to prevent identity leakage between training and testing.

Preprocessing converts each segmented iris into a fixed-size rectangular template using Daugman's rubber sheet model [13], which remaps the annular iris region from Cartesian coordinates to normalized polar coordinates so that pupil dilation and camera distance no longer change the image geometry:

$$I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta) \quad (11)$$

$$x(r, \theta) = (1 - r)\cdot x_p(\theta) + r\cdot x_i(\theta), \quad y(r, \theta) = (1 - r)\cdot y_p(\theta) + r\cdot y_i(\theta) \quad (12)$$

Here r lies between 0 and 1, θ is the angle, and the subscripts p and i denote points on the pupil and iris boundaries. Eyelids, eyelashes and specular reflections are masked, and pixel values are scaled to a common range before the tensors are passed to the CNN.

Data preparation followed a fixed sequence. Images were first screened for blur, occlusion and poor illumination; segmentation then separated the iris from the pupil, sclera and eyelids; normalisation produced the polar template; and contrast enhancement and denoising reduced residual differences between devices. Class labels were encoded for the two-neuron Softmax layer, and augmentation (small rotations and brightness changes) was applied to training images only, so that validation and test images remained unchanged and the estimates of generalization were not inflated.



(a) CASIA (b) MMU (c) Kaggle

Fig. 5. Samples of the iris datasets obtained from the (a) CASIA, (b) MMU and (c) Kaggle repositories.

Table 3. Summary of the datasets

Dataset summary	**Metric**
Volume of datasets utilized	10,000
Repositories utilized	3 (CASIA, MMU, Kaggle)
Training: validation: testing ratio	70: 10: 20
Images for training/validation/testing	7,000 / 1,000 / 2,000
Images from CASIA / MMU / Kaggle	3,700 / 3,150 / 3,150

The Component Design Phase

The component design follows OOADM and is expressed in four UML views. The **use case design** (Fig. 6) involves three actors: the user, the CNN model and the verifier. The user initializes the application, registers and logs in, builds the CNN from convolutional, pooling, flattening, and dense layers, trains it on preprocessed iris data, tests it on unseen images, detects age, views results, and checks the accuracy; the verifier matches the result against the recorded accuracy. The **class diagram** (Fig. 7) centres on a Model Initialization class that is specialized by Train Model and Test Model; these use a Detect Age class that works with a Classify_IrisData class and produces Results, each carrying attributes such as code, input value, weight and condition together with their setter methods.

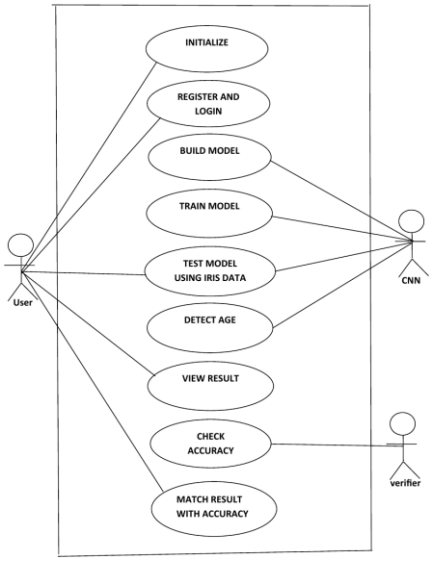


Fig. 6. Use case design of the proposed model.

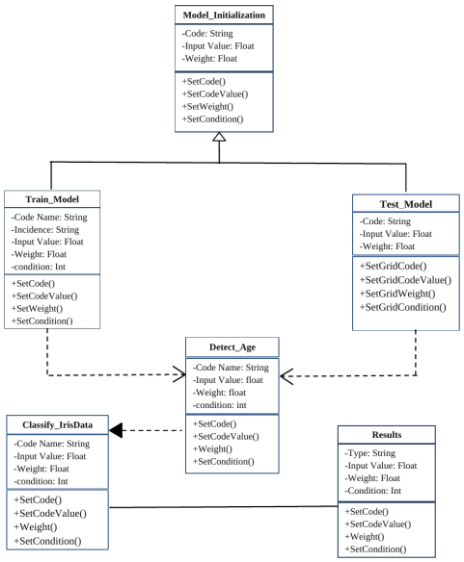


Fig. 7. Class diagram of the proposed model.

The **sequence diagram** (Fig. 8) shows the registrar entering the iris image and voter data, the preprocessing and CNN pipeline segmenting and classifying the image, the voting access control querying the registry, and the decision (eligible or flagged) returned to the user and logged. The **activity diagram** (Fig. 9) starts at image capture, preprocesses the image through segmentation and normalization, extracts features with the CNN, classifies age, and tests whether age is 18 or more; an eligible voter is accredited, and an underage voter is denied accreditation and displayed as such. A database design supports these views by storing user, iris, prediction, and audit records in MySQL.

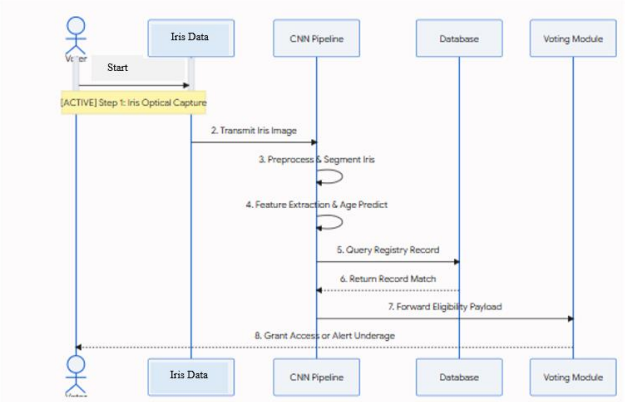


Fig. 8. Sequence diagram of the proposed system.

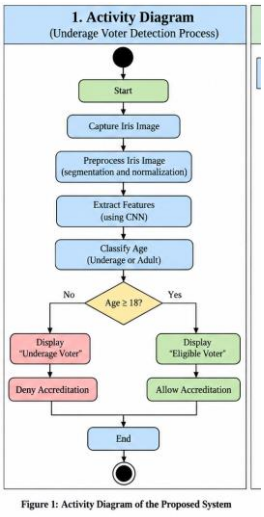


Fig. 9. Activity diagram of the proposed model.

Advantages of the Proposed System

i) **Automatic age screening** from iris texture removes dependence on declared age, certificates and manual checks.
ii) **End-to-end learning** by the CNN removes manual feature engineering and improves discriminative power over SVM-based pipelines.
iii) **Reduced latency and larger data scale**, since a normalised, GPU-trained CNN was trained on 10,000 images against 1,716 for the existing system.
iv) **Identity management and security** through registration, login, role-based access, audit logs and cloud-backed storage.
v) **A flexible, modular interface** and an object-oriented design that is reusable, maintainable and easy to extend.
vi) **Decision support for officials**, since suspected underage voters are flagged for further verification instead of being rejected automatically.

RESULTS AND DISCUSSION

The study achieved four results, corresponding to the four objectives: (i) a developed model for detecting underage voters; (ii) training, validation and testing of the model with a CNN on iris data; (iii) implementation of the model with Python, JavaScript, PHP and MySQL; and (iv) performance evaluation with a confusion matrix and a comparison with the existing system.

Developed Model for Detecting Underage Voters

A conceptual and computational model was developed with experimental research design, a machine learning pipeline and object-oriented design. The task was framed as supervised binary classification in which iris images are the inputs and the age categories under 18 and 18 and above are the targets, which keeps the research problem, the legal threshold, the CNN output and the evaluation criteria consistent. The experimental design defined the variables, the CNN configuration, the training, validation and testing procedures and the metrics; keeping each person's images in one partition guarded against identity leakage, and error analysis separated minors misclassified as adults (false negatives) from adults misclassified as minors (false positives), which carry different consequences for voter eligibility screening. The pipeline moved each image through acquisition, quality assessment, preprocessing, segmentation, normalisation, feature extraction, classification and decision-making, and the object-oriented design supplied modular, reusable components with defined responsibilities.

Training of the Model and Validation and Testing with Iris Data

The CNN was trained to separate minors from adults using convolution, ReLU activation, pooling, flattening and fully connected layers, with two output neurons for Softmax classification. The dataset was divided into

training, validation and testing subsets (Table 3) so that the first set estimated parameters, the second guided model selection and monitoring of generalisation, and the third measured performance on unseen data. Training ran for 300 epochs with the Adam optimiser and categorical cross-entropy loss. Table 4 and Fig. 10 show that the training loss fell from 0.6869 to 0.4145 and the validation loss from 0.6869 to 0.4151, with the gradient norm decreasing from 0.5032 to 0.0334. The two loss curves stayed almost identical throughout, which indicates stable convergence without a widening gap between training and validation loss, and the shrinking gradient shows that the weights were settling near a minimum.

Table 4. Training log of the CNN at selected epochs (300 epochs)

Epoch	Training loss	Validation loss	Gradient norm
1	0.6869	0.6869	0.5032
25	0.5747	0.5749	0.3735
50	0.5102	0.5104	0.2785
100	0.4518	0.4521	0.1651
150	0.4299	0.4303	0.1049
200	0.4207	0.4211	0.0697
250	0.4165	0.4170	0.0478
300	0.4145	0.4151	0.0334

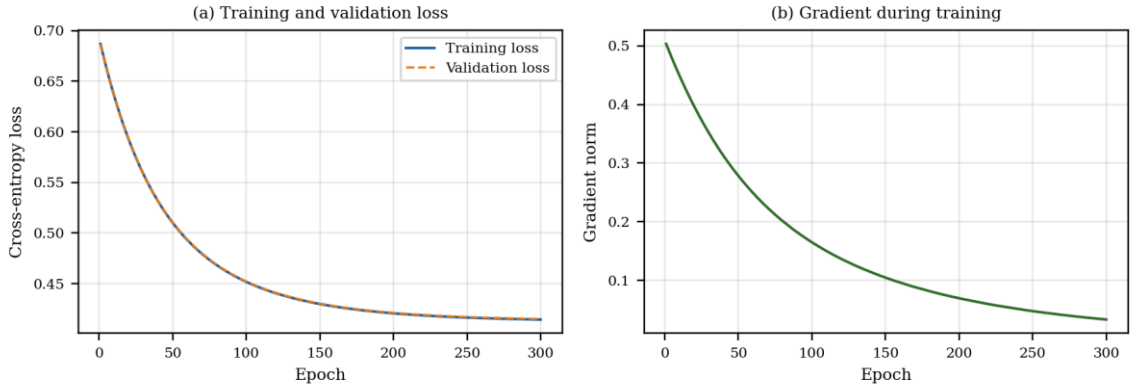


Fig. 10. Training behaviour of the CNN over 300 epochs: (a) loss, (b) gradient norm.

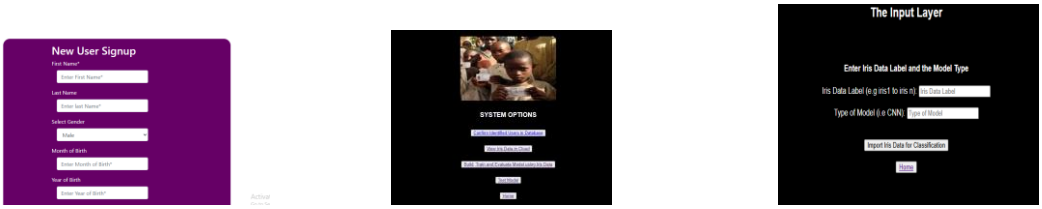
Implementation with Python, JavaScript, PHP and MySQL

The machine learning component was implemented in Python on Google Colab (Table 5), while the API at the front end was built with JavaScript and PHP and the records were managed in MySQL. The welcome page introduces the system and links to registration, login and system information (Fig. 11a). New users register by supplying identification, contact and iris data, and the API validates the entries to prevent duplicates, incomplete records and invalid formats (Fig. 11b); existing users log in with registered credentials before reaching the biometric functions. The options page (Fig. 11c) lets authorised users confirm identified users in the database, view iris data in the cloud, build, train and evaluate the model, and test it by importing an iris image with its data label for classification. Authentication, validation and role-based access address the identity-management gap and the rigid interface of the existing system.

Table 5. Implementation tools and system requirements

Item	Specification
Machine learning back end	Python 3 on Google Colab (GPU/TPU), TensorFlow and Keras, NumPy, OpenCV, Matplotlib
Front end and API	JavaScript and PHP served through XAMPP and a web browser
Database	MySQL relational database management system
Storage	Cloud storage and Google Drive for iris images

Item	Specification
Hardware	Laptop, smartphone or desktop computer with at least 2 GB RAM; optional external keyboard and mouse
Connectivity	Internet service



(a) Welcome page (b) Registration page (c) System options

Fig. 11. Screens of the implemented application.

Performance Evaluation Using a Confusion Matrix and Comparative Analysis

The model was evaluated with a confusion matrix on a 300-case example in which the positive class is under 18, with 200 true adults and 100 true minors. Of the 200 adults, 197 were classified as adults (true negatives) and 3 were flagged as minors (false positives); of the 100 minors, 98 were flagged (true positives) and 2 were missed (false negatives) (Table 6, Fig. 12). The metrics follow Eqs. (13) to (17):

Table 6. Binary classification confusion matrix (n = 300)

Actual / predicted	Adult	Under 18	Row total
Actual adult	TN = 197	FP = 3	200
Actual under 18	FN = 2	TP = 98	100
Column total	199	101	300

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) = 295/300 = 98.33\% \quad (13)$$

$$Precision = TP / (TP + FP) = 98/101 = 97.03\% \quad (14)$$

$$Recall = TP / (TP + FN) = 98/100 = 98.00\% \quad (15)$$

$$F1 = 2 \cdot Precision \cdot Recall / (Precision + Recall) = 196/201 = 97.51\% \quad (16)$$

$$FPR = FP / (FP + TN) = 3/200 = 1.5\% \quad (17)$$

Specificity is 98.50%, the false negative rate is 2.00%, the balanced accuracy is 98.25% and the classification error is 1.67%. The system therefore flags almost all minors (98 of 100) while wrongly flagging only 1.5% of adults. In an electoral setting this balance matters: a missed minor undermines the register, whereas a wrongly flagged adult is referred for further verification and is not automatically excluded.

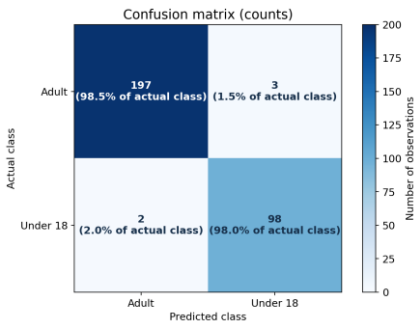


Fig. 12. Confusion matrix (300 cases).

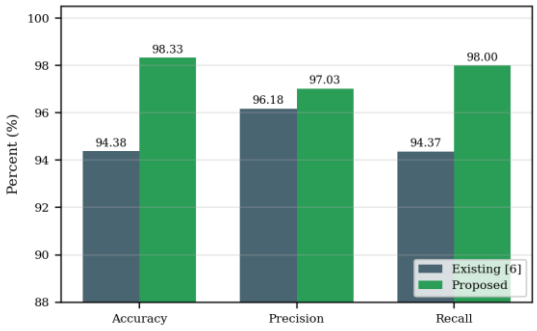


Fig. 13. Existing against proposed system.

The comparative analysis used dataset size, accuracy, speed, FPR, precision, and recall (Table 7, Fig. 13). The proposed system used 10,000 images against 1,716 and improved accuracy from 94.38% to 98.33% (3.95 percentage points), recall from 94.37% to 98.00%, and precision from 96.18% to 97.03%. Its FPR fell from 5.61% to 1.5%, and its processing time fell from 44.23 s to 28.57 s, a reduction of about 35%. The gains are consistent with the design choices: end-to-end CNN learning replaces separate feature extraction and SVM classification, batch normalization and dropout stabilize training, and a larger, more varied dataset supports generalization, which addresses the latency and scalability limitations identified in Section 3.3.

Beyond the headline figures, two observations support the design. First, the high recall (98.00%) matters more than raw accuracy for this application, because the cost of an undetected minor is borne by the integrity of the whole register. Second, the low FPR (1.5%) keeps the burden on registration officers manageable, since only a small fraction of adults would be referred for secondary verification. A receiver operating characteristic (ROC) analysis and the area under the curve (AUC) would require per-sample prediction scores across thresholds, and this is recommended for the field-validation stage.

Table 7. Comparison of the existing system [6] and the proposed system

S/N	Parameter	Existing system	Proposed system
1	Dataset records utilised	1,716	10,000
2	Accuracy of model	94.38%	98.33%
3	Speed (seconds)	44.23	28.57
4	False positive rate (FPR)	5.61%	1.5%
5	Precision	96.18%	97.03%
6	Recall	94.37%	98.00%

These findings must be read within the limits of the experiment. The 98.33% accuracy comes from a 300-case illustrative evaluation with assumed counts and not from an independently authenticated field test, so it does not guarantee equal performance in Nigerian registration centres, where image quality, devices and demographics vary. In addition, the existing system predicted age groups and gender while the proposed system performs a binary under-18 decision, so the comparison is indicative and not like-for-like. The classification errors also show that the system is best used as decision support, with flagged applicants referred for further verification, rather than as an autonomous arbiter of eligibility.

SUMMARY, CONCLUSION AND RECOMMENDATIONS

Summary

This study examined underage voting in Nigeria and proposed an AI-based detection system that uses iris biometric data and a CNN to identify persons under 18. An integrated methodology of experimental research, a machine learning pipeline, and OOADM was used to analyze, design, develop, and implement the system, with UML diagrams describing its structure and behavior. Iris images from CASIA, MMU, and Kaggle (10,000 images split 70:10:20) were preprocessed through resizing, normalization, segmentation, and denoising and used to train an AlexNet-based CNN with batch normalization, dropout, and Softmax output for 300 epochs. The system was implemented with Python, JavaScript, PHP and MySQL, and evaluated with a confusion matrix, giving 98.33% accuracy, 97.03% precision, 98.00% recall and 97.51% F1-score on the illustrative 300-case evaluation, and it outperformed the existing iris-based system on accuracy, recall, precision, FPR and speed.

Conclusion

Integrating iris biometrics with a CNN helps to detect underage voters during registration and verification by combining biometric imaging, preprocessing, deep feature learning, database management, and an application interface in one verification system. The reported accuracy reflects the dataset and conditions of this study and should not be taken as a guarantee of equal performance in varied real-world environments; the system is therefore better suited as a decision-support and verification tool than as an infallible autonomous one. The study concludes that CNN-based iris analysis offers a promising approach to strengthening voter-age verification and reducing underage registration, although extensive field validation is still required.

Recommendations

1) INEC should consider integrating AI-assisted iris age verification as an additional layer in voter registration and accreditation.
2) Larger and more demographically diverse iris datasets should be developed to improve generalisability and robustness.
3) The system should undergo extensive field validation under varied acquisition and operational conditions before large-scale deployment.

4) Future work should compare AlexNet with contemporary CNN and other deep learning architectures for accuracy and computational efficiency.
5) Standardised, high-quality iris capture devices and procedures should be adopted to limit the effect of poor image quality.
6) Strong cybersecurity, privacy, encryption, access control and audit mechanisms should protect stored biometric and voter data.
7) Multimodal approaches that combine iris data with other biometric or demographic information should be investigated.

Contributions to Knowledge

1) **A new standalone model for age detection using CNN and iris data.** The study extends iris biometrics beyond identity recognition to AI-assisted age-category classification for voter eligibility verification.
2) **An integrated system architecture** that links iris acquisition, preprocessing, CNN classification, eligibility decision-making, user interaction and data management.
3) **An end-to-end CNN-based framework** that learns discriminative iris representations automatically and reduces reliance on manual feature extraction and conventional classifiers.

REFERENCES

[1] Federal Republic of Nigeria, Constitution of the Federal Republic of Nigeria, 1999 (as amended), Sec. 29(4)(a).
[2] Federal Republic of Nigeria, Electoral Act, 2022.
[3] J. Alphonsus, F. Lambert, and F. Melinda, "The adoption and challenges of electronic voting technologies within the South African context," Int. J. Manag. Inf. Technol. (IJMIT), vol. 5, no. 4, pp. 1–12, 2021.
[4] N. Odebode, E. Akinkuotu, O. Aluko, and E. Opara, "ICYMI: I was almost killed for rejecting underage voters, says ex-INEC commissioner," The PUNCH, Feb. 19, 2018.
[5] Punch, "Practice, problems and prospects," Developing Country Studies, vol. 4, no. 2, 2022.
[6] B. I. Faluyi, A. O. Ojo, and O. O. Atobatele, "Development of iris based age and gender detection system," Int. J. Progressive Sci. Technol., vol. 34, no. 1, pp. 49–72, 2022, doi: 10.52155/ijpsat.v34.1.4477.
[7] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015.
[8] M. Muhammad, M. Nur, O. Ghazali, and H. Siti, "Age group classification using convolutional neural network (CNN)," J. Phys.: Conf. Ser., vol. 2084, p. 012028, 2021, doi: 10.1088/1742-6596/2084/1/012028.
[9] G. Angeline and O. Keerthiga, "Underage driving detection - age recognition using face detection," Int. J. Wavelets, Multiresolution Inf. Process., vol. 1, no. 1, pp. 1–17, 2021.
[10] B. Falohun, U. Precious, and M. Yemi, "Fingerprint-based age and gender detector system using fingerprint pattern analysis," in Proc. 5th Nat. Symp. NSF REU Res. Data Sci., Syst., Secur. (IEEE), 2020, pp. 2564–2571.
[11] P. Nwankwo, "Predictive model for detecting underage voters using deep learning and blockchain technology," in Proc. Int. Conf. Advancement Elect. Electron. Eng. (ICAEEE), Gazipur: IEEE, 2023, pp. 24–27.
[12] O. Kennedy, J. Samuel, O. Etinosa, and N. Charles, "An enhanced voters registration and authentication application using iris recognition technology," Int. J. Civil Eng. Technol. (IJCIET), vol. 10, no. 2, pp. 57–68, Feb. 2019.
[13] J. Tania and K. Pooja, "Iris segmentation and normalization using Daugman's rubber sheet model," Int. J. Sci. Tech. Advancements, vol. 1, no. 1, pp. 11–14, 2015.
[14] P. Machala, U. Sondos, and M. Blessing, "Criminal face detection system using the Fisherface algorithm and the Local Binary Patterns Histogram (LBPH) classifier," in Proc. 7th Int. Annu. Eng. Seminar, Yogyakarta, 2023.
[15] V. Felix, L. Georgina, and U. Marcus, "DeepUAge: Improving underage age estimation accuracy to aid CSEM investigation," ResearchGate, 2020.
[16] P. Emmanuel, "The issue of combating age fraud in the Nigerian civil service," 2020.

[17] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," Commun. ACM, vol. 60, no. 6, pp. 84–90, 2017.
[18] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," arXiv:1412.6980, 2014.
[19] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," in Proc. 32nd Int. Conf. Mach. Learn. (ICML), 2015, pp. 448–456.
[20] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: A simple way to prevent neural networks from overfitting," J. Mach. Learn. Res., vol. 15, pp. 1929–1958, 2014.
[21] Chinese Academy of Sciences, Institute of Automation, "CASIA iris image database," online dataset repository.
[22] Multimedia University, "MMU iris database," online dataset repository.