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DESIGN OF A CNN-BASED IRIS BIOMETRIC FRAMEWORK FOR UNDER-AGEVOTER SCREENING: INTEGRATION OF EXPERIMENTAL DESIGN, MACHINE LEARNING PIPELINES, AND OBJECT-ORIENTED MODELLING

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ABSTRACT
This article synthesizes the architecture and design contribution of a doctoral study proposing an iris-image convolutional neural network (CNN) to screen for possible underage voter registration. The work integrates experimental design, a reproducible machine-learning pipeline, and object-oriented software modelling. The proposed input–preprocessing–feature-learning–classification sequence includes quality screening, normalization, convolution/ReLU blocks, max pooling, flattening, dense feature integration, and two-class softmax inference. A human-review pathway is incorporated to prevent an uncertain biometric prediction from being treated as proof of legal age. The source thesis provides detailed architectural descriptions and worked performance calculations, but the available evidence does not independently verify population-level age discrimination from iris texture. The principal contribution is therefore a specified, testable research architecture and a validation protocol, not demonstrated operational eligibility determination. Recent literature on iris recognition, segmentation, generalization, and responsible AI is used to identify required controls before deployment.

Keywords: iris biometrics; convolutional neural network; underage voting; age-category screening; experimental design; reproducibility; machine learning; electoral integrity

INTRODUCTION
The doctoral thesis defines the voting-age threshold as 18 years and proposes iris-image classification as a supporting signal rather than a legally conclusive age certificate. This distinction is essential: iris texture is well established for identity recognition, but a model that identifies an iris does not thereby establish chronological age (Nguyen et al., 2024; Yin et al., 2025).
Current literature emphasizes robust segmentation, cross-sensor transfer, and the hazards of acquisition artifacts. Sumi et al. (2024) systematically compared iris segmentation methods; Lin et al. (2026) examined cross-domain segmentation; and Guo et al. (2025) explored dual-spectral localization. These studies support careful preprocessing, not an assumption that age can be read deterministically from iris structure.
For transparent model development, data provenance, target definition, participant grouping, prespecified metrics, and external validation must be explicit. TRIPOD+AI provides useful reporting principles even though it was designed for clinical prediction research (Collins et al., 2024). PROBAST+AI similarly offers transferable lessons about bias and applicability (Moons et al., 2025).
The paper addresses the research question: how can a proposed iris-based age-category screening system be specified and assessed without conflating iris identity recognition with biological age inference? This distinction matters in electoral contexts because a false adult prediction for a minor and a false minor alert for an adult have different procedural consequences.

Statement of the Problem
The thesis identifies attempted registration or voting by persons below the legal age as a problem for electoral credibility. Conventional identity checks may confirm that a person matches a record while leaving the reliability of the recorded birth date unresolved. A proposed CNN iris classifier is

intended to provide an additional screening signal; however, identity biometrics alone do not verify date of birth.

The central scientific gap is a lack of documented evidence that the particular iris images used for the proposed classifier contain a stable, generalizable signal distinguishing ages 4–17 from ages 18 and above. Confounding from sensor type, illumination, image editing, subject identity, repeated files, and age-folder construction may create apparent predictive success without genuine age sensitivity.

The source thesis also juxtaposes a standalone system scope with descriptions of PHP, JavaScript, MySQL, and centralized registration screens. A rigorous article must distinguish implemented components from intended integration and avoid converting diagrams or screenshots into proof of deployment (Nguyen et al., 2024; ISO/IEC, 2023).

Research hypothesis: a CNN may be trained to discriminate the labelled groups within a dataset; the distinct and stronger hypothesis that it generalizes to unseen people and real electoral conditions requires independent validation.

Aim and Objectives

Aim: To formulate and critically assess a CNN-based iris screening framework for possible underage voter registration, with clear separation of architectural specification, model fitting, and evidential validation.

Objectives

1: Specify image acquisition, age-label provenance, preprocessing, quality assurance, CNN feature learning, and threshold-based classification.
2: Integrate experimental controls, subject-disjoint dataset partitioning, repeatable training, and documented model selection into the pipeline.
3: Describe object-oriented modules for dataset handling, preprocessing, training, prediction, audit logging, and optional user-interface/database services.
4: Define a reproducible evaluation protocol and characterize the consequences of false positives, false negatives, calibration error, and dataset shift.
5: Identify the evidence that would be necessary before an iris-based model could responsibly inform voter-registration screening.

Significance of the Study

The technical contribution is an explicit integration of experimental design, the machine-learning life cycle, and modular software engineering. This integration reduces ambiguity about which stage produces which artifact and makes it possible to audit data leakage and model updates (Collins et al., 2024; Moons et al., 2025).

The methodological contribution is a distinction between biometric recognition and age-category inference. Iris recognition research has strong evidence for matching identities; the transfer of that evidence to chronological-age classification is not automatic. A carefully specified negative result can be as scientifically informative as a positive one (Yin et al., 2025; Azizi & Charalambous, 2026).

The policy relevance lies in designing an advisory, reviewable signal rather than an automated disenfranchisement mechanism. A screening alert should prompt verification of official age documentation and permit appeal; it should not independently determine voting rights. The NIST AI RMF and ISO/IEC risk-management guidance offer useful governance concepts (NIST, 2023; ISO/IEC, 2023).

The work also creates a basis for future replication through data manifests, image hashes, code versions, seeds, split records, training logs, checkpoint hashes, and saved held-out predictions.

Related Works (2023–2026): Iris Recognition and Segmentation

Nguyen et al. (2024) surveyed deep learning for iris segmentation, recognition, presentation-attack resistance, and forensic applications. Their synthesis establishes that iris recognition is a mature biometric research area, while leaving open the separate task of predicting legal-age categories.

Sumi et al. (2024) benchmarked segmentation methods across datasets and documented why boundary localization matters. Salve and Narote (2024) proposed segmentation and classification using an attention-based recognition framework. Neither study should be interpreted as proof that iris texture determines chronological age.

Yin et al. (2025) reviewed datasets and deep-learning methods for iris identification and segmentation. Luo et al. (2025) investigated channel/spatial attention, while Guo et al. (2025) examined multiscale dual-spectral segmentation. Lin et al. (2026) addressed domain-invariant segmentation, and Azizi and Charalambous (2026) reviewed feature-extraction approaches.

Across these works, recognition accuracy is task-specific: a model may identify an eye with high accuracy while failing to distinguish whether its owner is below or above 18.

Recent work	Research focus	Relevance / limitation
Nguyen et al., 2024	Deep iris-recognition survey	Recognition ≠ age estimation
Sumi et al., 2024	Segmentation benchmarks	Preprocessing robustness
Yin et al., 2025	Iris deep-learning review	Dataset and task definitions
Lin et al., 2026	Cross-domain segmentation	Domain-shift risk

Related Works (2023–2026): Reliability and Governance

Collins et al. (2024) updated transparent reporting guidance for prediction models, emphasizing clear participant selection, data sources, model specification, and evaluation. Moons et al. (2025) introduced PROBAST+AI for bias and applicability appraisal. Although developed for health prediction, both are useful methodological analogies for the current high-stakes screening task.

The NIST AI RMF (2023) and ISO/IEC 23894:2023 describe lifecycle risk assessment; ISO/IEC 42001:2023 provides organizational AI management-system requirements. The European Union AI Act (2024) further illustrates why consequential biometric applications demand legal and fundamental-rights scrutiny. These sources concern governance, not proof of classifier accuracy.

The literature gap is therefore sharply defined: contemporary iris studies establish segmentation and identity recognition performance, but the thesis does not cite a large, externally validated study demonstrating that iris images alone accurately distinguish 17-year-olds from 18-year-olds under deployment conditions.

Consequently, any positive result must be tested against trivial baselines, acquisition confounding, subject overlap, and a near-threshold age subgroup before it is framed as a contribution to electoral age screening.

Methodology: Integrated Research Design

Experimental design defines the testable target: $y=1$ if independently verified chronological age is below 18, otherwise $y=0$. A prospective protocol specifies recruitment, ethical approval, image capture, age-document verification, sample-size justification, and split criteria before model fitting.

The machine-learning pipeline consists of image intake, quality assessment, duplicate hashing, subject grouping, iris localization/normalization, training-only augmentation, convolutional feature learning, validation-based model selection, and held-out evaluation. All fitted transformations must be learned exclusively from training data.

Object-oriented design maps the stages into cohesive classes: DatasetRegistry, ImageQualityController, IrisPreprocessor, SplitManager, CNNClassifier, ExperimentRunner, Evaluator, and AuditLogger. Interface contracts allow replacement of CNN backends without changing the evidence chain.

This combination is an architecture and evaluation plan derived from the thesis, not evidence that every software class has already been executed or integrated into a production system.

Design layer	Primary artifact	Control
Experimental	Protocol + hypotheses	Pre-registration
ML pipeline	Data/model artifacts	Leakage prevention
Object-oriented	Modules + interfaces	Traceable state
Governance	Review and appeals	Human oversight

METHODOLOGY

CNN Architecture and Equations

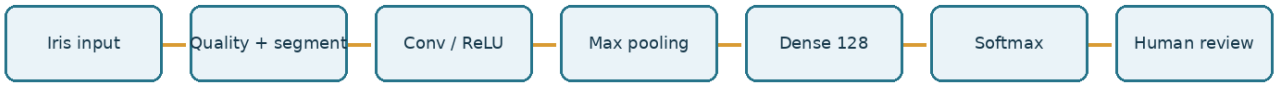
The thesis proposes successive convolution and rectified linear unit (ReLU) transformations followed by max pooling, flattening, a fully connected layer with 128 units, and a two-unit softmax output. Input dimensions and kernel specifications must be reported with the actual executed model configuration.

For input feature map X and kernel K, convolution at spatial location (i,j) is $Z(i,j,k)=b_k+\Sigma_u\Sigma_v\Sigma_c K(u,v,c,k)X(i+u,j+v,c)$. ReLU produces $A=\max(0,Z)$. Max pooling reduces the spatial grid by retaining the maximum activation within each pooling window.

The flattened vector f feeds $h=\mathrm{ReLU}(W_1 f+b_1)$; class logits are $z=W_2 h+b_2$; softmax gives $p_k=\exp(z_k)/\Sigma_j \exp(z_j)$. For one-hot target y, categorical cross-entropy is $L=-\Sigma_k y_k \log(p_k)$. The Adam optimizer updates parameters using minibatch gradients.

Prediction uses a prespecified minor-alert threshold τ. If $p(\text{minor})\geq\tau$, the system emits an advisory minor alert; otherwise it emits an adult prediction. Low-quality or uncertain inputs should abstain and request document-based verification.

Figure 1. Proposed CNN inference pipeline (author-designed schematic).



RESULTS AND DISCUSSION

Architecture-Level Findings

Result 1—model specification: the thesis defines a coherent CNN pipeline for binary classification of iris images and articulates experimental, computational, and object-oriented components. This is a design result, not a demonstrated age-inference result.

Result 2—traceability: the framework can connect each input image to preprocessing, model version, threshold, and decision record. Such traceability supports debugging and retrospective auditing when implemented.

Result 3—evaluation readiness: the thesis presents formulas and illustrative confusion-matrix counts. Their numerical consistency can be checked, but no claim of validated population performance follows without accessible age-labelled, subject-independent held-out predictions.

The most serious validity threat is that a CNN could memorize subjects, acquisition sessions, or image manipulations rather than age. A further threat is a possible discontinuity at age 18 that the iris itself may not encode. Strong claims require a prospective test near the legal threshold.

Evidence category	Available from thesis	Permitted inference
CNN design	Architecture description	Framework specified
Worked confusion matrix	300 illustrative cases	Arithmetic demonstration
Age estimation validity	No independent proof	Not established
Operational election use	No field trial	Not established

DISCUSSION

Limitations, and Implications

The thesis establishes an intelligible research concept but contains a critical gap between classification architecture and verified chronological-age inference. Iris texture is a strong identity feature; it is not a certified biological clock. The research must test whether observed group separation persists across different people, cameras, ethnic backgrounds, and capture conditions (Nguyen et al., 2024; Lin et al., 2026).

The highest-risk errors occur close to the legal cutoff: a minor classified as adult may bypass a screening alert, while an adult classified as minor may be subjected to unnecessary scrutiny. Therefore, sensitivity at ages 16–17, specificity at ages 18–19, uncertainty estimates, and a documented appeals process should receive more attention than aggregate accuracy alone.

The manuscript also distinguishes a software prototype from an operational electoral system. Deployment would require security testing, privacy impact assessment, retention controls, institutional authorization, lawful basis for biometric processing, and a policy against automatic denial of voting rights based on a classifier (NIST, 2023; European Parliament & Council, 2024).

Recommended next experiment: collect an adequately powered, independently verified and subject-identified cohort; freeze a protocol; evaluate on an external acquisition site; report confidence intervals, calibration, and performance by age and acquisition conditions.

SUMMARY AND CONCLUSION

This article extracts and refines the doctoral thesis into a research-ready account of CNN-based iris age-category screening. The strongest defensible achievement is the specified integration of experimental controls, machine-learning stages, and auditable software components. The available material does not yet establish that iris texture alone can reliably determine whether an individual is below 18 years of age. Any real-world use should remain advisory and require independently verified age records and human review. Future work must prioritize verified labels, subject-disjoint external testing, and transparent reporting.

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