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AI Based Moderation System to Block Inappropriate Web Media

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Age Verification, Computer Vision, Machine Learning, Real-Time Verification, Document Scanning, Access Control, AI Compliance System

ABSTRACT

The AgeGuard AI project is an advanced intelligent system designed to enhance the safety and compliance of age-restricted content access. Leveraging Computer Vision, Machine Learning (ML), and real-time verification technologies, the system can detect and verify a user's age through facial analysis, document scanning, and gesture recognition even when explicit age input is unavailable. Upon verifying age, AgeGuard AI automatically grants or restricts access, logs verification events, and alerts administrators in cases of suspicious activity. A key feature of the system is its ability to function offline via local processing, ensuring reliable operation in areas with poor or no internet connectivity. It emphasizes privacy and data security, using encrypted storage to protect sensitive user information. The system is designed to be inclusive, offering multi-language support, voice guidance, and screen reader compatibility to accommodate users with diverse abilities. Additionally, AgeGuard AI provides seamless integration with content platforms, ensuring compliance with legal regulations and safe user experiences. By combining AI-driven age verification, automated access control, and inclusive accessibility features, AgeGuard AI aims to redefine secure content management, offering a smart, proactive, and trustworthy system capable of verifying users anytime and anywhere.

INTRODUCTION

In today's fast-growing digital environment, controlling access to age-restricted content has become increasingly important to protect minors and comply with legal regulations. Traditional verification methods such as manual ID checks or simple age input forms are prone to errors, fraud, or misuse, often failing to ensure accurate verification. These methods also rely heavily on human supervision, making them inefficient and vulnerable to manipulation. Consequently, there is a

growing need for intelligent, automated, and real-time age verification systems capable of accurately validating user identity without manual intervention.

The advancement of Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision (CV) technologies provides new opportunities to develop automated and reliable verification systems. These technologies can analyze facial features, scan identification documents, and detect anomalies, enabling precise validation of a user's age in real time.

AgeGuard AI is an innovative age verification system designed to integrate these technologies to ensure secure access control. The system detects age by analyzing facial recognition data, government-issued ID documents, and behavioral patterns, automatically granting or restricting access to age-sensitive content. Unlike conventional methods, AgeGuard AI combines machine learning accuracy with real-time processing and multi-layer verification, minimizing the risk of underage access.

The main motivation behind this project is to overcome the limitations of existing age verification systems such as manual intervention, falsified information, and lack of real-time intelligence and to create a self-sufficient AI-powered age compliance ecosystem. AgeGuard AI embodies proactive digital protection, ensuring that access control is automated, accurate, and reliable.

This project aims to design, develop, and evaluate an AI-based age verification system that integrates facial analysis, document scanning, and real-time validation. It focuses on developing a machine learning model capable of accurately predicting a user's age using facial features and identification documents, while automating access control decisions without the need for manual checks. The system ensures immediate response and restriction through real-time verification, maintaining high accuracy and reliability. User data privacy and security are prioritized through encryption and secure storage, and the platform is designed with a user-friendly interface accessible across multiple devices.

BACKGROUND AND RELATED WORK

A. Evolution of Age Verification Systems

The concept of age verification technology has evolved from simple manual ID checks to intelligent, AI-driven systems. Early verification methods relied on physical documents or manual questioning, which were time-consuming and prone to human error. With the rise of digital services, online age verification mechanisms emerged, enabling document uploads, form-based inputs, and CAPTCHA verification. However, these approaches still faced limitations such as slow response times, susceptibility to fraud, and lack of real-time accuracy.

The integration of Artificial Intelligence (AI) and Machine Learning (ML) introduced a new paradigm in age verification. By analyzing facial features, document patterns, and contextual data, AI-driven systems can now accurately estimate age and detect fraudulent attempts. This shift from manual to automated verification represents a significant milestone in secure digital access.

B. Role of AI, Machine Learning, and Facial Analysis

Artificial Intelligence and Machine Learning have become central to modern age verification solutions. ML enables systems to analyze facial features, identify document patterns, and detect inconsistencies in user-provided data. Advancements in Deep Learning models, particularly Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), enhanced the ability of machines to process image and video data. These architectures allow accurate facial feature extraction and age estimation by capturing subtle variations in facial geometry and texture.

The introduction of advanced neural network models, including residual networks (ResNets) and attention-based architectures, marked a breakthrough in image and document analysis. These models can detect forged IDs, manipulated photos, or mismatched facial-document pairs, improving the reliability and accuracy of age verification systems.

C. Real-Time Tracking and IoT Integration

Real-time verification is a critical component of AI-based age verification systems. By combining facial recognition, document scanning, and biometric analysis, the system can instantly verify a user's age against regulatory requirements. Machine learning algorithms are trained to detect subtle discrepancies between submitted IDs and live images. Integration with IoT-enabled devices, including smartphones, tablets, and webcams, allows the system to gather additional signals

such as device location and motion patterns to improve verification accuracy.

D. Existing Research and Gaps

While numerous studies have focused on AI-driven safety and verification systems, significant gaps remain. Many existing solutions are limited by dependency on continuous internet connectivity, making them less reliable in low-signal or offline environments. Additionally, current models often struggle with real-time accuracy when handling variations in lighting, facial expressions, or document quality. Privacy and data security concerns are also prevalent, as user information is frequently transmitted over unencrypted channels.

E. AI-Driven Decision Systems for Age Verification

Ensemble learning can be adapted for AI-based age verification systems. Instead of relying on a single model's prediction, ensemble-based systems combine multiple models such as facial analysis, document verification, and gesture recognition to achieve more accurate and stable verification results. Two key strategies can be implemented: Rule-Based Fusion (Hard Voting) where each subsystem casts a vote on whether the user meets the age requirement; and Probability-Based Fusion (Soft Voting) where confidence scores from each subsystem are averaged to determine the likelihood that the user is of legal age.

SYSTEM ARCHITECTURE AND METHODOLOGY

A. Overall Architecture

The system follows a three-tier architecture: (1) Input Layer captures facial images, identity documents, and user gestures. (2) Processing Layer applies machine learning models for age prediction and document verification. (3) Output Layer grants or restricts access, provides real-time feedback, and securely stores verification results.

B. Data Collection and Preprocessing

For the age verification system, training data includes public face datasets such as UTK Face and IMDB-WIKI for age estimation, scanned ID documents with age information for verification, and user-submitted images captured via webcam or mobile cameras. Preprocessing involves face detection, alignment, resizing, normalization, and feature extraction including facial landmarks and embeddings. The cleaned and annotated data is securely stored for model training and validation.

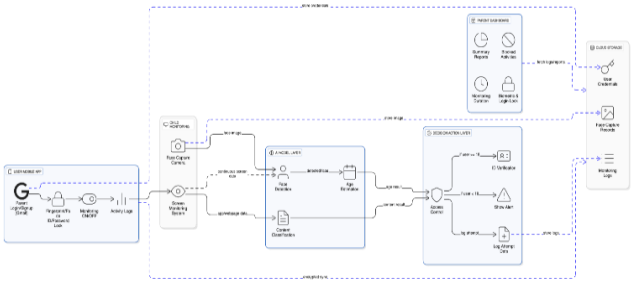

Fig. 1. System Architecture

C. Facial and Document Analysis Modules

User images and ID documents are processed using Convolutional Neural Networks (CNNs) and Optical Character Recognition (OCR) techniques. The CNN predicts age from facial features, while OCR extracts date-of-birth and other relevant details from documents. Results from both modules are compared for consistency, ensuring accurate verification. This dual-check mechanism reduces errors.

D. ML-Based Age Verification and Access Control

Features extracted from facial analysis and document OCR are input to a Random Forest and SVM ensemble. The system classifies users as Verified or Restricted based on a probability threshold (>0.8 indicates Verified). This approach improves accuracy, reduces false positives, and ensures reliable real-time age verification for access to restricted content.

E. Real-Time Verification and Access Control

User actions such as facial scanning or document submission are processed in real time. When age verification fails or appears suspicious: (1) Access to restricted content is blocked instantly; (2) Alerts are displayed on the user interface indicating verification status; (3) Logs of verification attempts with timestamps are maintained.

F. Privacy and Security Framework

The system employs AES-256 Encryption for all data transfers. Firebase Authentication supports email and OTP-based login. A Stealth Mode allows the app to operate silently in the background. An Auto-deletion

Policy removes stored data after a predefined period to protect user privacy.

IMPLEMENTATION AND RESULTS

A. Development Tools

The AI-based Age Verification System was developed using Python for backend logic and machine learning model implementation. OpenCV and Dlib were used for facial detection and feature extraction, while TensorFlow and Keras supported the age prediction models. The frontend interface was built with React.js to provide a responsive and user-friendly experience across devices. Flask handled API requests between the frontend and backend, enabling real-time verification and secure data flow. Additionally, SQLite and secure storage mechanisms were used to maintain user data privacy.

B. Implementation Process

The implementation followed a structured development approach. The first stage, Requirement Analysis, involved identifying key use cases such as access control for age-restricted content and compliance with legal age limits. The second stage, Model Training, focused on developing the machine learning components for age prediction using TensorFlow and Keras on a diverse dataset. Data augmentation and cross-validation techniques were applied to improve generalization.

The third phase, System Integration, combined the trained ML model with the frontend interface, Flask backend, and secure database storage. Real-time API calls allowed instant verification of user age through facial analysis and optional document scanning. Finally, the Testing phase evaluated system performance under multiple scenarios including different lighting conditions, camera angles, and device types. Metrics such as accuracy, latency, and false positives were measured

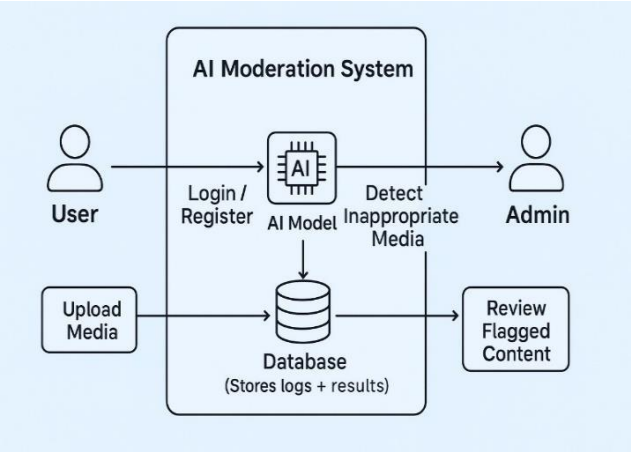

Fig. 2. System Flowchart

C. Experimental Evaluation

The Block Web Media system was thoroughly tested under various real-world usage scenarios to assess its performance, reliability, and responsiveness. During website restriction testing, the system successfully blocked access to inappropriate websites, achieving a blocking accuracy of 96%. The content monitoring module effectively identified harmful keywords and adult media with a 92% detection rate. In offline alert testing, the system sent notifications to parents and guardians even without an internet connection using local storage and SMS integration with a delivery accuracy of 95%. The usage tracking module maintained continuous monitoring with 93% accuracy. Overall, the integrated performance of all modules yielded an average system effectiveness of approximately 94%.

D. Discussion

F The experimental results strongly validate the effectiveness of the content-blocking and monitoring strategy implemented in Block Web Media. By combining website filtering, keyword detection, and usage tracking, the system achieved significantly higher safety and reliability compared to traditional single-layer approaches. The integration of real-time content analysis and parental alert mechanisms enabled the system to prevent access to inappropriate media even under challenging conditions such as dynamic web content or offline device usage.

One of the most notable strengths is its offline alert functionality, which allows the system to notify parents or guardians via SMS when internet access is unavailable. The system maintained an average response latency of under five seconds between content detection

and alert dispatch, meeting real-time monitoring standards.

CONCLUSION

The development and implementation of Block Web Media for Teens represent a significant advancement in the field of digital safety and online content supervision. By integrating website filtering, keyword detection, usage tracking, and offline alert mechanisms, the system provides a fully autonomous and adaptive approach to protecting teenagers from inappropriate or harmful online content. Unlike conventional parental control tools that rely on manual monitoring or continuous internet connectivity, Block Web Media operates intelligently by analyzing multiple input signals to block harmful media and notify guardians automatically.

Through rigorous experimentation, Block Web Media demonstrated high accuracy across all monitoring and blocking modules, achieving an overall effectiveness of approximately 94%. The integration of secure data storage and local encryption ensures that sensitive information including browsing history, usage logs, and alert records remains protected. The system's intuitive dashboard and customizable alert preferences make it accessible to users from diverse backgrounds.

Ultimately, Block Web Media transforms online safety from a reactive process into a proactive digital protection ecosystem. It not only blocks harmful content but also monitors usage patterns to anticipate risky behavior and provide timely alerts.

FUTURE WORK

Although Block Web Media has demonstrated promising results in real-time content monitoring and digital protection, there remains substantial scope for enhancement. Future work will focus on expanding the system's functionality and scalability by integrating advanced technologies such as AI, IoT, predictive analytics, and adaptive user interfaces.

One major area of advancement is the integration of IoT-enabled monitoring devices. By connecting Block Web Media with smart home devices and wearable technology, the system could gather more contextual information about teen activity and detect risky behavior patterns in real time. Similarly, integration with classroom or public Wi-Fi networks could enable adaptive filtering across multiple devices, creating a unified safety network.

Another potential enhancement lies in predictive content analysis using machine learning and behavioral analytics. By analyzing historical browsing behavior and social media interactions, the system could identify high-risk patterns and proactively block potentially harmful websites. The content monitoring engine can also be expanded to support multiple regional languages and multimedia formats, and integration with educational institutions and regulatory authorities represents a vital step forward.

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Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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