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Comparative Performance Evaluation of Real-Time Webcam and HOG-Based Facial Recognition Systems for Children's Screen Time Management

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Abstract

This research examines two distinct facial recognition methods: a real-time webcam-based system utilizing a custom dataset and an approach employing Histogram of Oriented Gradients (HOG) with the Olivetti dataset. The study focuses on evaluating the accuracy and efficiency of these methods in facial recognition tasks. The webcam-based system demonstrated strong proficiency in live environments, accurately identifying individual children and dynamically updating their screen time, showcasing real-time adaptability and personalized monitoring. Its performance is illustrated through screenshots displaying the interface, where individualized screen time percentages are overlaid on the children's faces. In contrast, the HOG method, applied with the Olivetti dataset, achieved a peak accuracy of 95.00% using optimal HOG parameters, reflecting its robust recognition capabilities. This study contributes to the field of screen time management by exploring how facial recognition technologies can support healthier digital habits among children. It highlights critical security and privacy considerations, particularly the responsible handling of facial data in environments accessible to minors. The study concludes that while both methods are effective, the real-time system offers superior adaptability for dynamic applications requiring continuous user monitoring. These findings advance the field of computer vision, offering insights into optimizing facial recognition technologies for practical and ethical applications.

I. INTRODUCTION

In the digital age, screen interactions have become an integral part of our daily lives [1]. While technology offers unprecedented access to information and connectivity, concerns surrounding its excessive use, particularly among children, are growing [2]. Excessive screen time has been linked to a myriad of developmental and health challenges in children, from impaired cognitive growth to sleep disorders [3], [4]. As parents and guardians grapple with the challenge of monitoring and managing screen time, there is a pressing need for innovative solutions that can aid in this endeavor.

Keywords Cybersecurity, facial recognition, histogram of oriented gradients (HOG), image processing, machine learning, real-time image processing

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Facial recognition technology, an evolving field in computer vision, presents a promising avenue to address this challenge. By accurately identifying and monitoring users, it offers the potential to automate screen time management, tailoring it to individual needs and predefined criteria. Additionally, the use of facial recognition technology raises important security and privacy considerations. Ensuring responsible management of facial data is essential to protect children's privacy and prevent misuse. According to a study conducted in 2020, primary school children faced significant challenges during distance learning in the Covid-19 pandemic [5]. The research, surveying parents in Muş, Turkey, revealed that most children exceeded the recommended two-hour daily screen time, with 79.1%.

Existing facial recognition systems, though advanced in accuracy and attendance tracking, largely overlook the complexities of real-time screen time monitoring, particularly the need for continuous engagement tracking, privacy safeguards tailored for children, and adaptability to dynamic usage scenarios. This paper focuses on evaluating and comparing two facial recognition systems, emphasizing their performance and adaptability in various real-world applications, with screen time management used as a primary example. Through the exploration of the Olivetti dataset [6] and the development of a face recognition system, this research aims to present a solution that ensures the responsible and beneficial use of screens, fostering a balanced digital environment for the younger generation. Additionally, by incorporating a custom dataset, the study further customizes the approach to screen time management, tailoring the solution to the specific needs and dynamics of individual families. The proposed study aims to close this gap by creating a face recognition-based screen time management system that is simple to use. This system will use innovative image processing and computer vision techniques to regulate screen time precisely, addressing the various needs of children while promoting responsible technology use. Furthermore, this study primarily focuses on evaluating the effectiveness of two distinct facial recognition systems: one utilizing the Olivetti dataset and another employing an original dataset coupled with real-time webcam-based recognition.

The two main research questions that form the framework of this study are as follows:

- How do the real-time webcam-based facial recognition system and the HOG-based system compare in terms of accuracy, efficiency, and privacy implications for user identification?
- What are the strengths, limitations, and ethical concerns of using facial recognition for a potential screen time managing system in dynamic and controlled environments?

This study focuses exclusively on children rather than adults because children are in critical developmental stages, making them more susceptible to the negative impacts of excessive screen time—such as cognitive delays, sleep disorders, and behavioral issues—while also lacking the self-regulation abilities that adults typically have, thereby necessitating external monitoring systems like the one proposed, which not only addresses these health concerns but also integrates privacy and ethical considerations tailored specifically to protect minors.

The key contributions of this study include a comprehensive comparison of two facial recognition methods—real-time webcam-based recognition using a custom dataset and a HOG-based approach with the Olivetti dataset—highlighting their respective strengths and limitations. It also demonstrates the integration and use of both a custom dataset for real-time recognition and the Olivetti dataset for HOG-based evaluation, emphasizing the performance differences between controlled and dynamic environments. Additionally, the study showcases a practical application of these facial recognition systems in managing screen time, illustrating their potential for broader real-world use cases.

In Section 2, this study provides a background, introducing foundational concepts related to facial recognition technology and concerns surrounding children's excessive screen time. Section 3 then delves into a literature review, analyzing prior research and advancements in the domain of cybersecurity and managing screen time for children. The methodology, detailed in Section 4, elucidates the technical specifics of the two facial recognition systems. This is followed by Section 5, where the experimental results are presented, showcasing the system's performance. Section 6 holds a discussion that evaluates the results of the research. The study concludes in Section 7, summarizing the key insights and suggesting avenues for future research.

II. Background

A. Introduction to Facial Recognition

Facial recognition technology, a key component in computer vision, has seen significant advancements in recent years. This technology involves the identification and verification of individuals from a digital image or video frame against a database. It has applications ranging from security systems to user authentication processes [7].

B. Screen Time and its Impact

1) Definition and types of screen time

Screen time refers to the amount of time spent using devices with screens, such as smartphones, tablets, computers, and televisions [8]. It is categorized into passive (watching TV, videos) and interactive (playing video games, using computers) screen time [9].

2) Effects of excessive screen time on health, especially in children.

Excessive screen time has been linked to various health issues in children, including impaired cognitive development, sleep disorders, and physical health problems like obesity [10], [11]. It can also affect social skills and mental health.

C. Security Implications of Facial Recognition

The use of facial recognition technology for managing children's screen time brings several security and privacy considerations. Ensuring that facial data is collected, stored, and managed responsibly is essential to protect the privacy of the children involved. Implementing basic security measures to safeguard this sensitive information is crucial to prevent potential misuse. Addressing these security implications is vital to maintaining the trust of users and ensuring the ethical use of the technology in environments where children are present.

Firstly, the collection of facial data must adhere to strict consent protocols. Parents and guardians should be fully informed about the nature of the data being collected, its intended use, and the measures in place to protect it. Clear and transparent communication about data usage policies helps in building trust with the users. Currently, robust encryption methods have not been implemented in this study, but they are planned for future work. Encrypting stored data is essential to protect it from unauthorized access and potential breaches. Continuous monitoring and updating of security protocols will also be necessary to safeguard against evolving cyber threats. Furthermore, access to the facial recognition system should be restricted to authorized personnel only. Implementing access controls and regular audits can help in ensuring that only individuals with legitimate reasons can access the data. This reduces the risk of internal misuse or accidental data leaks.

In addition to technical measures, there should be comprehensive policies and procedures for data handling and disposal. Once the facial data is no longer needed, secure deletion methods must be employed to ensure that no residual data can be recovered. By integrating these security considerations into the development and implementation of facial recognition systems, it can be ensured that the technology is used ethically and responsibly, thereby providing a safe and secure solution for managing children's screen time.

D. Facial Recognition Algorithms & Techniques

1) Overview of traditional and current facial recognition algorithms.

Facial recognition technology has progressed from traditional methods like geometric feature-based approaches and the Eigenface method, which utilized principal component analysis, to advanced techniques such as 3D facial recognition, Convolutional Neural Networks (CNNs), and Histogram of Oriented Gradients (HOGs) [12]. These developments have markedly improved accuracy, speed, and scalability. Modern algorithms are more adept at handling variations in lighting, pose, and facial expressions, with HOGs providing robust feature extraction by analyzing the distribution and direction of gradients [13]. Today's systems often blend these methods, combining 3D models with CNNs and HOGs for enhanced classification, and are increasingly integrated with other biometrics for comprehensive security solutions and applications in smart technology [14].

2) Introduction to Histogram of Oriented Gradients and their significance in facial recognition.

The Histogram of Oriented Gradients is a feature descriptor crucial in computer vision, particularly in facial recognition. It operates by dividing an image into small regions or cells and computing histograms of gradient directions within these cells [15]. This approach effectively captures the structure and shape of objects, particularly human faces, by emphasizing edge and gradient orientation. HOGs are known for their robustness in capturing facial features, making them highly effective for face detection.

In facial recognition, HOGs are valued for their resilience to variations in lighting and contrast, focusing on the contrast and spatial structure of facial features. They excel in delineating facial structures like the jawline, nose, and eyes, crucial for accurate recognition [16]. Additionally, HOGs can be integrated with other machine learning techniques, such as Support Vector Machines (SVMs), enhancing their effectiveness [17]. Their application extends to various real-world scenarios, including security systems and consumer electronics, underscoring their significance in modern facial recognition technology.

E. Technical Environment & Libraries

In developing the facial recognition system, several essential libraries and tools were utilized, anchored by Python as the primary programming language. OpenCV [18], crucial for image processing and computer vision tasks, was paired with the face recognition library for efficient and accurate facial detection. NumPy [19], renowned for its array handling and mathematical capabilities, played a vital role in data manipulation and computation. Matplotlib [20] was employed for visualizing data and results, enhancing the interpretability of the system's performance. The scikit-learn library (sklearn) [21] provided robust machine learning algorithms for face recognition and model evaluation. Additionally, the 'time' library was integral for managing usage durations and enforcing time limits.

For the development workflow, PyCharm [22] was the chosen Integrated Development Environment (IDE), providing advanced coding and debugging features, while Anaconda [23] streamlined the management of library dependencies. This ensemble of Python, OpenCV, face recognition, NumPy, Matplotlib, sklearn, 'time', PyCharm, and Anaconda formed a cohesive and robust foundation, crucial for the successful development and implementation of the facial recognition system aimed at effective screen time management.

F. Datasets in Facial Recognition

While datasets like VGGFace2 and LFW are well-known for their diversity and real-world applicability [24, 25] it was the Olivetti dataset, with its distinct set of facial images, that underpinned our system's training and testing phases [6].

It features 400 gray-level images representing the faces of 40 distinct individuals. Each person is depicted through ten different images, capturing variations in lighting, facial expressions, and details, all set against a uniform black background. The images, each of a size of 64x64 pixels, provide a comprehensive basis for the system's training and validation. The identities of the individuals in the dataset are anonymized and encoded as integers ranging from 0 to 39. In terms of system performance, the facial recognition model achieved a commendable accuracy score of 0.94.

Its contribution has been vital in enhancing the accuracy and robustness of our model, providing a controlled environment that allowed for focused analysis and optimization. This dataset's unique composition of facial expressions and configurations offered a well-defined framework for advancing our facial recognition technology, ensuring our system was effectively trained to recognize and manage screen time efficiently in targeted scenarios.

III. Literature Review

The literature review delves into a series of previous studies focusing on the application of face recognition-based systems, showcasing their evolution and diverse applications.

A. Recent Studies on Cybersecurity and Privacy for Children

Recent studies have highlighted various aspects of cybersecurity and privacy related to children's use of digital technologies. A study titled "Information Technologies Exposing Children to Privacy Risks: Domains and Children-Specific Technical Controls" addresses the need for privacy controls specifically tailored to children[26]. The authors identify 25 technical controls designed to protect children's privacy and classify them through NIST Security and Privacy control categories and Hoepman's privacy design strategies. The study highlights that most controls focus on age identification and authentication, with a preference for minimization techniques over hiding, separating, and aggregating data.

The study underscores the limitations of generic privacy controls, which often fail to adequately protect children. It emphasizes the need for technical measures compliant with stringent legal obligations like the EU GDPR. The findings reveal that children can easily bypass age verification mechanisms or inadvertently consent to privacy policies they do not understand, highlighting the necessity for more effective, children-specific controls. This research provides valuable insights for system engineers and developers, aiming to enhance digital privacy and security for young users by proposing a comprehensive framework for implementing tailored technical measures.

Another notable study, "Child Access Control Based on Age and Personality Traits," proposes a method to control children's access to the Internet by considering multiple personality traits (such as age, eye diseases, heart diseases, and neurological and psychological conditions) using a Mamdani-based fuzzy logic inference system [27]. The input parameters of this system are described by five linguistic parameters—"very low," "low," "medium," "high," and "very high"—with a triangular membership function. This approach focuses on the individual user, providing a tailored solution for managing children's Internet access. This research is particularly significant for parents, guardians, and those responsible for children's well-being, offering a more nuanced method for controlling exposure to harmful online content and excessive digital device use.

Moreover, in the article "The Two Faces of the Child in Facial Recognition Industry Discourse: Biometric Capture Between Innocence and Recalcitrance," the authors explore the discursive construction of facial recognition technology as it pertains to children [28]. Based on data from facial recognition tradeshows and interviews with industry members, the study examines how children are portrayed in the promotion of facial recognition technology. The authors argue that the industry presents children as both innocent and recalcitrant, exploiting this tension to legitimize and expand the use of facial recognition technology. This dual portrayal highlights the challenges and ethical considerations involved in the biometric monitoring of children, acknowledging the fast-changing nature of children's appearances as a technical challenge.

These studies collectively provide an overview of the current landscape in cybersecurity and privacy frameworks, focusing on protecting children online.

B. Face Recognition Systems and Managing Screen Time

Firstly, in the study, ""Children''s Face Recognition Based on Convolutional Neural Network,"" Jiali Zhang et al. explore the realm of children''s face recognition using advanced deep learning techniques [29]. Utilizing the ORL children''s face database, the team trained a model with 500 facial images of 50 children, using CNNs and the Keras framework. This innovative approach enabled the model to efficiently perform multiple tasks concurrently, including face recognition authentication and attribute classification. The study focused on optimizing the model to enhance classification accuracy under the constraint of limited data support, addressing inefficiencies found in existing deep learning frameworks for children''s face recognition.

The research yielded promising results, demonstrating high accuracy in the recognition of children's faces, which indicates its potential for practical applications, particularly in video-based detection and recognition. The model's effectiveness in this domain underscores the viability of CNNs in improving face recognition systems, even with limited datasets. However, the study also acknowledges the challenges and areas for improvement in the field of children's face recognition using CNNs. While the CNN approach improves recognition accuracy, the study neglects real-time constraints and lacks a comprehensive privacy framework essential for applications involving children. Future research directions highlighted by Zhang et al. include refining the network training process, improving handling of large and complex datasets, and addressing the specific challenges posed by children's face recognition, thus paving the way for more advanced and accurate recognition systems.

Secondly, Dulyawit Prangchumpol introduces a novel attendance system using face recognition in "Face Recognition for Attendance Management System Using Multiple Sensors," [30]. The system operates in five stages: capturing student faces in various expressions, using the efficient Haar cascade technique for face detection, evaluating the captured face against stored data, saving the attendance results to Google Cloud, and displaying results. The research employs Android's face recognition, a deep learning technique, combined with OpenCV on the Android OS. Tools like JDK, JRE, and OpenCV Manager support the system. The paper tests its model on 25 subjects and finds it to be the most accurate, with the highest training time, compared to other methods. While integrating multiple sensors enhances face detection accuracy, the system does not consider user interaction or screen engagement levels, which are crucial for effective screen time management. In conclusion, the system enhances traditional attendance methods by integrating real-time face recognition and allowing students easy data access and modification via Google Cloud.

Furthermore, Shun Lei Myat Oo et al.'s study, "Child Face Recognition with Deep Learning" offers a comprehensive examination of the accuracy and performance of CNNs [31]. Given the significance of face recognition in applications such as locating missing children and ensuring school safety, the researchers aimed to identify the most efficient network for distinguishing young faces. Children, unlike adults, present unique challenges in facial recognition due to subtle age-related features. To address this, the authors employed three notable CNNs: VGG Face based on VGG16 and ResNet50 architectures, and MobileFaceNet. Their methodology, implemented using Keras and TensorFlow, rigorously tested these networks on a child face dataset. The findings were unequivocal: MobileFaceNet outperformed its counterparts, achieving a stellar recognition accuracy of 99.75%. This research underscores the potential of leveraging deep learning techniques, particularly MobileFaceNet, for enhancing child face recognition capabilities. Despite achieving high accuracy with MobileFaceNet, the system prioritizes recognition performance over real-world applicability, omitting considerations for privacy, ethical concerns, and continuous monitoring challenges.

Additionally, the study titled "A Robust Technique of Face Recognition Algorithm for Automated Attendance Management System," Sekar. R et al. put forth an innovative robotized participation board framework [32]. The core of this framework is centered around face identification and acknowledgment algorithms. When a student enters the classroom, this system captures their image, identifies them based on their facial features, and marks their attendance. The comprehensive framework design and the intricate calculations utilised at each stage are detailed extensively in the paper. The system structure, as illustrated in Figure 1, is rooted in a face recognition algorithm. The authors discuss the various stages in this computerised assistance management system, from image capture to face detection and recognition. The Viola-Jones detection algorithm, known for its efficiency, was chosen for this system due to its robust performance under varied lighting conditions. Post-processing involves translating recognised faces into an Excel sheet and notifying absentees. However, the proposed system is not without challenges. Spoofing is a significant concern, and the researchers propose using an eye blink detector to counter such threats.

The paper also touches upon the development of a database, emphasising the importance of capturing images under different angles, expressions, and lighting conditions. The database for this study comprised images of 80 individuals. Feature extraction and classification play pivotal roles in the system's accuracy. Techniques like Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Local Binary Pattern Histogram (LBPH) are explored, with LBPH showing promise in real-time situations with high detection rates and low false positives. The conclusion underscores the efficiency of the proposed system, highlighting its high detection rates and low false positives, especially when using the LBPH algorithm. Future work aims to enhance the system's adaptability to various face angles and integrate stride recognition for improved performance. Limitations include challenges in recognising facial variations beyond 30 degrees and changes in individual appearance, such as facial hair or wearing a scarf.

Furthermore, the study titled "Principal Component Analysis Algorithm for Face Recognition in Kindergarten Students" by Ahmad Abul Khair and Muhammad Ibnu Sa'ad presents a tailored face recognition system designed for young children in educational environments [33]. Acknowledging the challenges teachers face in manually monitoring kindergarten students, the authors developed an automated system utilizing the Viola-Jones method for initial face detection, followed by feature extraction using Principal Component Analysis (PCA). This approach enabled real-time face recognition with notable accuracy, even when accounting for the unique facial features and expressions of young children. The system was tested with 70 training images (five per child) and achieved a 91.42% accuracy rate when applied to 14 new images. Euclidean Distance was employed to match faces accurately. The study highlights the system's practical applications in classroom settings, particularly for attendance tracking, while addressing challenges such as variations in facial expressions and lighting conditions. This research provides valuable insights into implementing efficient and lightweight face recognition systems in early childhood education, supporting educators in managing classrooms more effectively. Despite achieving reasonable accuracy using PCA, the study overlooks real-time adaptability and struggles with varying facial expressions and lighting conditions, limiting its utility for dynamic screen time monitoring.

In addition, the research "Exploring Facial Recognition Technologies for Classroom Management" by R. Nidhya et al. introduces an advanced facial recognition system designed to automate attendance tracking with high precision and efficiency [34]. Leveraging OpenCV and deep learning-based face recognition algorithms, the system facilitates real-time student detection and identification, achieving an impressive 99.38% accuracy rate. The methodology includes systematically capturing images, applying segmentation techniques, and extracting unique facial features for model training. Beyond identifying student presence, the system logs attendance data with precise timestamps, creating a comprehensive database that aids in monitoring attendance trends over time. The study also places significant emphasis on ethical considerations, ensuring explicit consent from participants and maintaining stringent data privacy measures. By integrating advanced image processing and machine learning techniques, this research demonstrates how AI-driven solutions can streamline classroom management, reduce administrative workloads, and enhance educational environments through accurate and efficient attendance monitoring. While the system demonstrates high accuracy in tracking student attendance, it lacks consideration for screen time management and fails to address critical privacy concerns in environments involving minors.

Finally, "Face Recognition Based Automated Attendance Management System" by Aparna Trivedi et al. addresses the challenges of traditional, time-consuming attendance marking methods in academic settings [35]. The paper introduces a face recognition-based system, leveraging high-definition video and IT tools, to streamline attendance recording. The motivation for this research stems from the limitations of prevalent methods such as clickers, ID card swipes, and manual logging, which can be easily manipulated.

The proposed system uses Python, the OpenCV library for image processing, and tools like the Raspberry Pi for capturing and storing images in a database, ensuring accurate and efficient attendance marking. This face recognition approach not only enhances classroom discipline but also promises reduced human error and greater accuracy. Although the use of the Viola-Jones algorithm and LBP histogram provides reliable attendance tracking, the system fails to accommodate dynamic environments, limiting its effectiveness for continuous screen-time monitoring. The paper concludes by highlighting the potential of face recognition algorithms and suggesting future research avenues, especially in enhancing the neural network classifier for better accuracy.

Table I presents a concise comparison of key studies in facial recognition and screen time management. It outlines the techniques used, summarizes the findings and results, and specifies the datasets employed in each piece of research.

In conclusion, advancements in face recognition technology have paved the way for innovative solutions to challenges in various domains. The studies highlighted emphasize the transformative potential of face recognition techniques, from optimizing classroom attendance procedures to understanding parental concerns during pandemic-induced distance learning. While the results, such as the 96.5% accuracy rate achieved by Zhang et al. in recognizing children's faces, are commendable, it's essential to consider the limitations and ethical concerns associated with such technologies. As technology continues to progress, it's crucial to balance innovation with ethical considerations, ensuring that solutions benefit the broader community without compromising individual rights or privacy.

TABLE I
COMPARATIVE OVERVIEW OF EXISTING RESEARCH

Studies/ Criteria	**Methodology/ Technique Used**	**Key Findings/ Results**	**Dataset Used**
Ahmad Abul Khair & Muhammad Ibnu Sa'ad (2024) [33]	Viola-Jones for face detection, PCA for recognition, Euclidean Distance	91.42% accuracy in kindergarten student recognition	70 images (5 per student) of 14 students
R. Nidhya et al. (2024) [34]	OpenCV, advanced image segmentation, CNN-based facial recognition	Achieved 99.38% accuracy in classroom attendance	Images of classroom students with time-stamped logs
Jiali Zhang et al. (2021) [29]	Convolutional Neural Networks (CNN)	Achieved 96.5% accuracy in recognizing children's faces	ORL children's face database: 500 images of 50 children
Dulyawit Prangchumpol (2019) [30]	OpenCV; Deep Learning	Achieved 97% accuracy; total training time of 182.01s	10 Images of each student that registered
Shun Lei Myat Oo et al. (2019) [31]	VGG16, ResNet50, MobileFaceNet; Keras; TensorFlow	Best recognition accuracy of 99.75% with MobileFaceNet	VGGFace
Sekar. R et al. (2019) [32]	Viola-Jones detection algorithm; Local Binary Pattern Histogram (LBPH)	High detection rates and low false positives with LBPH	Images of 80 individuals
Aparna Trivedi et al. (2022) [35]	OpenCV; Viola-Jones technique; LBPH algorithm;	Improved accuracy (almost 100%) in attendance tracking	Images of the students

IV. METHODOLOGY

The methodology of this study is designed to evaluate two separate facial recognition systems aimed at managing screen time for children. The first system uses real-time facial recognition comparing with a custom dataset, while the second system is more technical, employing explicit HOGs to analyse and compare facial features against the Olivetti dataset.

Different datasets were intentionally used for each system to align with their specific operational contexts and testing goals. The real-time webcam-based system required a custom dataset to capture dynamic, real-world conditions, including varied lighting, angles, and facial expressions, which are essential for evaluating live recognition performance. This custom dataset consisted of 35 images (5 per child) from 7 children, reflecting the challenges of real-time data collection where maintaining consistent lighting, camera angles, and user cooperation limited the ability to gather a large volume of images. Conversely, the HOG-based system was tested using the Olivetti dataset, comprising 400 grayscale images of 40 individuals (10 images per person), chosen for its standardized nature and suitability for controlled experiments focused on static image recognition. The larger scale of the Olivetti dataset enabled comprehensive testing and parameter tuning of the HOG method, offering insights into its capability to handle diverse facial images—something that would not have been feasible with the smaller, real-time dataset. This approach allowed for a more accurate assessment of each system within its intended application environment.

A.System Development for Real-Time Identification

1) Dataset Creation

The first system utilizes a custom dataset comprising photographs of seven children, with five images for each. These images captured a range of angles, including front-facing, side profiles, and 45-degree angles, to ensure comprehensive facial feature representation. This process is exemplified in Fig. 1. It is important to note that all images were obtained with the explicit consent of the parents, each signing a consent form.

To ensure consistency and accuracy during real-time data collection, several quality control measures were implemented. Images were captured under uniform lighting conditions to minimize shadows and glare. Camera angles were standardized across sessions to ensure consistent facial feature representation, and each subject was recorded multiple times from different angles to capture variations in facial expressions and head positions. These measures ensured the reliability and accuracy of the custom dataset used for real-time facial recognition.

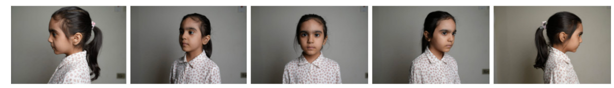

Fig. 1. Training Samples from Custom Dataset

2) Development Environment

The development environment, consisting of PyCharm and Anaconda, provides a comprehensive and integrated programming suite. This environment uses real-time image capture from a webcam to identify children based on a custom image dataset. Additionally, it enhances user interaction by overlaying a square on the detected person's face, complemented by a percentage display at the bottom, indicating the remaining screen time available to the user. This visual feedback mechanism is pivotal for informing users about their current screen time usage in an intuitive manner.

Fig. 2 shows the comprehensive workflow of the facial recognition system designed for screen time management. The flowchart details each step in the process, starting from capturing the user's face using a camera, to recognizing the face and determining whether it matches a known user in the dataset. It further delineates the decision-making

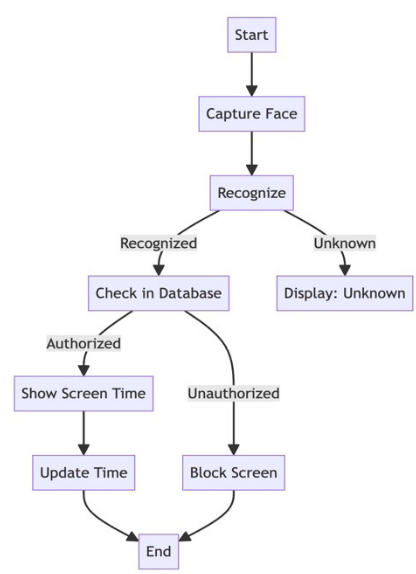

Fig. 2. Flowchart of the Facial Recognition System for Screen Time Management Process

process based on whether the face is recognized. For recognized users, it checks their allotted screen time, and depending on whether their time limit has been reached, the system either allows continued use or blocks access to the device. In cases where the face is not recognized, the system displays an ‘Unrecognized User’ message. This flowchart effectively encapsulates the operational logic of the system, illustrating how it manages screen access based on user identification and time tracking.

3) Image Preprocessing

In the webcam-based facial recognition system, the preprocessing steps are tailored to prepare real-time video frames for efficient facial recognition. The key preprocessing technique involves resizing each video frame to one-fourth of its original size. This step significantly reduces the computational load, allowing for faster processing without compromising the effectiveness of face detection and recognition. Additionally, the system converts the color space of each frame from BGR to RGB. OpenCV captures images in BGR format, while the face recognition library used operates on RGB images. This color space conversion is essential for the compatibility and accuracy of the facial recognition process.

4) Facial Recognition Implementation

The facial recognition implementation for the real-time system is accomplished with Python and a suite of associated libraries. OpenCV is used for video frame capture and initial processing, while the face_recognition library, supported by NumPy for data handling, performs the facial feature comparison against the custom dataset. Dlib’s machine learning algorithms are also leveraged indirectly through face_recognition for accurate face detection and recognition, making it possible to validate a user’s identity and manage their screen time effectively.

B.System Development for HOG-Based Analysis

1) Dataset Processing

The Olivetti dataset was selected for its consistent and standardized image set, which offers a controlled environment ideal for benchmarking facial recognition algorithms. While modern datasets like VGGFace2 offer more diversity, the Olivetti dataset’s simplicity and balanced composition allow for focused performance evaluation without the complexities introduced by large-scale, variable datasets.

This facial recognition system was systematically partitioned to facilitate robust training and validation. Specifically, the data was divided such that 80% was dedicated to training, allowing the algorithms to learn and adapt to facial features, while the remaining 20% was reserved for testing. This split ensured that the models were not only trained on a comprehensive set of images but also evaluated on a distinct subset to accurately gauge performance and generalization capabilities.

A sequence of grayscale images representing one individual’s facial variations are shown in Fig. 3. The first eight images are designated for training the facial recognition algorithm, while the last two are used for testing.

Fig. 3. Training and Testing Samples from the Olivetti Dataset

2) Programming Environment

For the HOG-based analysis system, Python’s scientific libraries, including NumPy and scikit-image, are explicitly utilized to perform detailed feature extraction through HOGs. Unlike the previous method where HOGs were an implicit part of the facial recognition process, this approach incorporates HOG descriptors directly within the code, allowing for hands-on experimentation with cell sizes to optimize feature detection. The methodology explicitly avoids real-time camera capture, instead scanning and analyzing pre-captured images from the Olivetti dataset, with a focus on the methodical tuning of HOG parameters to refine the facial recognition model’s accuracy.

3) Image Preprocessing

For the facial recognition system utilizing the Olivetti dataset and HOG, preprocessing is minimal due to the nature of the dataset. The Olivetti images are already provided in a preprocessed form – they are grayscale, normalized, and of uniform size (64x64 pixels), making them immediately suitable for further processing. The primary preprocessing task in this code is the application of the HOG descriptor, a feature extraction technique that analyzes the gradients and edge directions within the image. This step is crucial in capturing the unique facial features necessary for effective facial recognition.

4) Facial Recognition Implementation

The HOG-based system is implemented to scan and compare facial features from the Olivetti dataset. This system focuses on the extraction and analysis of detailed facial structures to create a robust recognition model.

Fig. 4 illustrates the streamlined sequence of operations in the facial recognition system using HOG, starting from loading the Olivetti dataset to plotting the accuracy results of the recognition process.

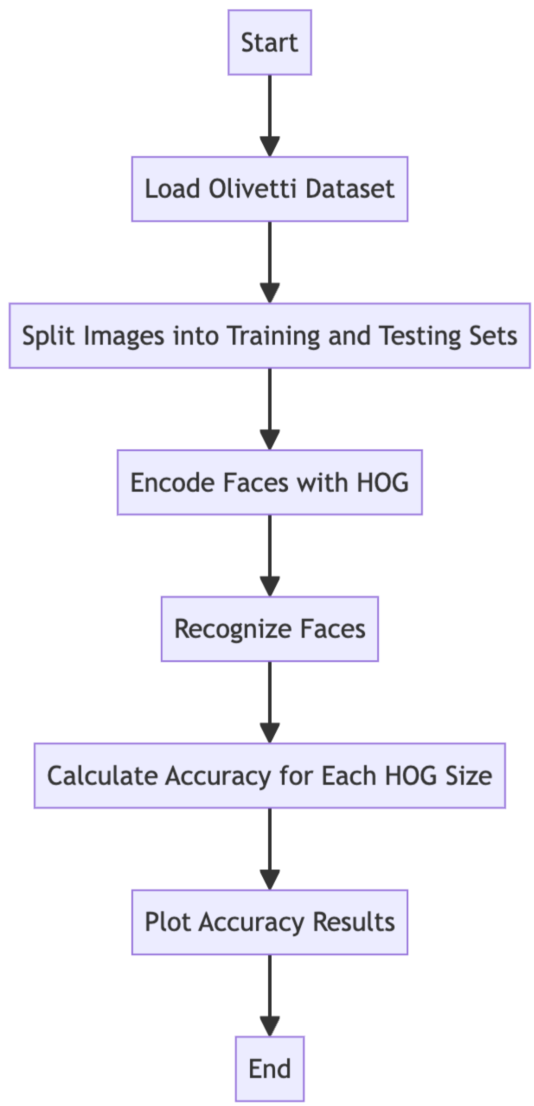

Fig. 4. Workflow of the HOG-Based Facial Recognition Process

5) Performance Evaluation

To comprehensively evaluate the performance of the facial recognition system, four standard classification metrics were used: (1) Accuracy, (2) Precision, (3) Recall, and (4) F1-Score.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Where: TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

Accuracy measures the overall correctness of the system by calculating the ratio of correctly identified faces to the total number of predictions. Precision evaluates how many of the system's positive identifications were correct, helping to minimize false positives. Recall (or Sensitivity) assesses the system's ability to correctly identify all relevant faces, focusing on minimizing false negatives. F1-Score balances Precision and Recall, providing a single metric that reflects the system's overall reliability, particularly in cases where there is an imbalance between false positives and false negatives. These metrics offer a holistic view of the system's effectiveness in real-world facial recognition tasks.

C. Experimental Setup

Each system is subjected to a rigorous experimental setup. For the real-time identification system, testing involves real-life scenarios with the children's photographs. For the HOG-based system, the Olivetti dataset provides a diverse range of faces for analysis. Both systems aim to showcase adaptability and accuracy in various conditions.

The experimentation phase assesses the accuracy of both systems by comparing recognition results with the known datasets. The real-time system is tested in varied lighting and environmental conditions to validate its practical applicability. The HOG-based system's efficacy is measured by its ability to distinguish between different individuals in the Olivetti dataset.

V. Results

This study evaluates two facial recognition methods for managing screen time: a facial recognition system with a small dataset and a classical HOG with the Olivetti dataset, focusing on the accuracy of each method under different conditions. The results aim to show each method's outcomes independently.

A. Facial Recognition with the Original Dataset

This method demonstrated decent accuracy during live trials with a webcam, correctly identifying each child and dynamically displaying their remaining screen time. Notably, the system adeptly managed individual sessions; it continuously updated and displayed the pertinent screen time for each child as they appeared or departed from the webcam's view, ensuring personalized time tracking.

Fig. 5. showcases several screenshots from the system in action, illustrating the facial recognition interface with overlaid squares on the children's faces and individualized screen time percentages. These images provide a clear visual representation of the remaining allowable screen time for each child. In the images, the child on the left is correctly identified by the system, displaying his name along with the percentage of screen time he has left. Meanwhile, the second child in the frame is flagged as having unauthorized access, highlighting the system's capability to distinguish between recognized and unrecognized individuals.

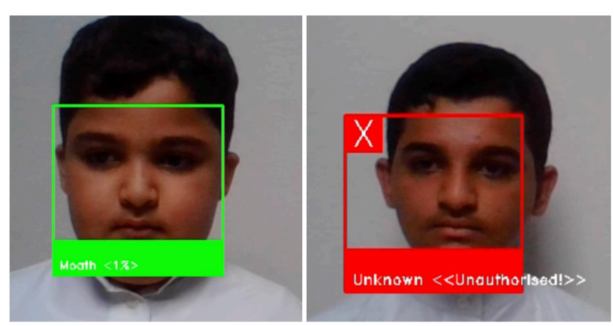

Fig. 5. Screenshots with Real-Time Screen Time Tracking

B. Histogram of Oriented Gradients with the Olivetti Dataset

The alternative approach applied the HOG method for feature extraction, in conjunction with the Olivetti dataset. The accuracy achieved with HOG descriptors was found to be highly dependent on the chosen descriptor size. Specifically, a HOG size of (8, 8) achieved an accuracy of 95.00%, indicating excellent recognition capability. At a HOG size of (16, 16), accuracy slightly decreased to 90.00%. Notably, a substantial decrease in accuracy to 10.00% was observed with a HOG size of (32, 32). Fig. 6 . displays the inverse relationship between HOG size and the system's accuracy. It clearly shows that larger HOG cell sizes significantly reduce the system's ability to identify and categorize faces correctly, highlighting the critical nature of selecting appropriate HOG parameters to ensure both accuracy and computational efficiency.

TABLE II
PERFORMANCE METRICS FOR DIFFERENT HOG SIZES

HOG Size				
(8, 8)	95.00	0.97	0.95	0.95
(16, 16)	90.00	0.93	0.90	0.89
(32, 32)	85.00	0.88	0.85	0.84

Table II presents the performance evaluation of the facial recognition system using varying HOG sizes. The (8, 8) configuration yielded the highest accuracy (95.00%), with strong precision (0.97) and recall (0.95), suggesting that smaller HOG cells capture finer facial details, enhancing recognition performance. As the HOG size increased to (16, 16) and (32, 32), a gradual decline in performance was observed, with accuracy dropping to 90.00% and 85.00%, respectively. Larger HOG cells tend to generalize more, leading to a loss of fine-grained features necessary for accurate facial recognition. This trend is also reflected in the F1-Score, which decreased from 0.95 to 0.84. These results highlight the importance of selecting optimal HOG parameters to balance computational efficiency and recognition accuracy.

C. Comparative Analysis of the Results

The real-time webcam-based system showcased strong adaptability in dynamic environments, successfully recognizing users under varying lighting and angles. However, its performance is constrained by the limited size of the custom dataset (35 images), which stems from practical challenges in real-time data collection, including maintaining consistent conditions and user cooperation. This limitation affects its scalability when compared to the HOG-based system, which was evaluated using the Olivetti dataset containing 400 images. The HOG-based method demonstrated higher recognition accuracy (95.00%) in controlled settings and benefited from the larger dataset, enabling extensive parameter tuning. However, it lacks the real-time adaptability of the webcam-based system, making it less suitable for dynamic, real-world applications.

VI. DISCUSSION

The discussion of the study's results can be approached by examining the performance of each facial recognition method and exploring the implications of these findings

A. Real-Time Facial Recognition with the Custom Dataset

This method demonstrated high accuracy in live environments, utilising a webcam for real-time identification. The system's ability to correctly identify each child and dynamically display their remaining screen time is a notable achievement. Such precision in real-time recognition and tracking indicates the system's robustness in handling variable environmental conditions, like lighting and background changes, which are common in real-world settings. The system was capable of managing individual sessions by continuously updating the screen time as children entered or left the camera's field of view. This feature not only enhances the system's utility in managing screen time but also ensures personalised monitoring. The interface efficiently communicates the remaining screen time, serving as an effective tool for both children and guardians to monitor and regulate screen usage.

B. Histogram of Oriented Gradients with the Olivetti Dataset

The results obtained using the HOG method with the Olivetti dataset reveal critical insights into the impact of HOG descriptor size on facial recognition accuracy. They suggest that the choice of HOG size is paramount in facial recognition, where smaller sizes are better for high-precision tasks, while larger sizes might be suited for general applications where detail is less critical. This observation suggests that in facial recognition technology, there is a significant trade-off between the detail of feature extraction and computational efficiency, influenced by the size of feature descriptors.

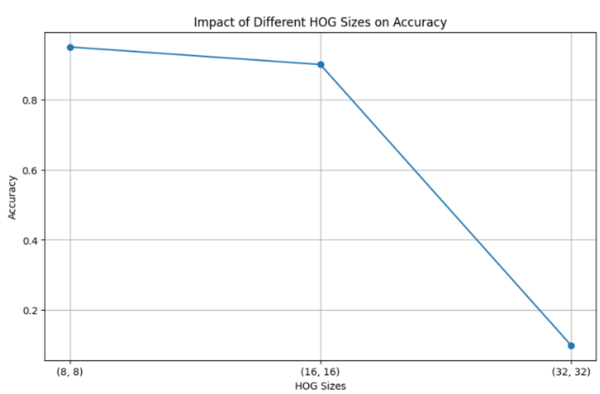

Fig. 6. Impact of Different HOG Cell Sizes on Accuracy

This inverse relationship between HOG size and accuracy, depicted in Fig. 6., suggests that larger HOG cells may overlook essential facial features, leading to misidentification. This finding is crucial for the practical application of HOG-based facial recognition, indicating that optimizing HOG parameters is vital for balancing accuracy and computational efficiency.

The use of facial recognition in screen time management provides significant benefits over conventional techniques. Traditional methods, such as parental control apps or device-level timers, often rely on manual inputs and can be easily bypassed by tech-savvy users. In contrast, facial recognition ensures continuous and automatic user verification, enabling accurate screen time tracking tailored to each individual. This approach enhances user accountability and offers a hands-free solution for parents and guardians seeking to manage children's screen usage effectively.

VII. Conclusion

This study focused on evaluating two facial recognition methods, assessing their accuracy and adaptability for user identification tasks in diverse applications, with screen time management serving as one demonstration of their potential use. The investigation yielded significant insights into the capabilities and limitations of these technologies for accurately identifying individuals and managing screen time.

The webcam-based system demonstrated noteworthy accuracy and real-time adaptability. It proved effective in recognising individual children and dynamically updating their screen time, thereby offering a personalised and interactive approach to screen time management. The interface, displaying real-time data on screen usage, underscores the system's potential as a practical tool. On the other hand, the HOG method, while showing high accuracy with smaller descriptor sizes, revealed a significant sensitivity to parameter selection. The marked decrease in accuracy with larger HOG sizes highlights the necessity of fine-tuning these parameters for optimal performance.

Future research could explore the integration of facial recognition systems with broader cybersecurity measures to enhance their reliability and security. For instance, combining facial recognition with multifactor authentication methods could provide a more secure and comprehensive solution for screen time management. Additionally, the technology could be adapted for use in other secure environments, such as educational institutions and childcare facilities, where controlling access and monitoring activities are critical. Research could also investigate the development of advanced algorithms that not only improve recognition accuracy but also reduce the computational load, making the system more efficient and user-friendly. These advancements would pave the way for safer and more effective use of facial recognition technology in various applications. Additionally, future research could focus on enhancing the systems' ability to differentiate between passive and interactive screen time. For the real-time webcam-based system, potential improvements include integrating eye-tracking technology to accurately detect user focus and engagement, distinguishing between active usage and passive presence. This would allow the system to identify when a user is physically present but not actively interacting with the content. These improvements would contribute to a more comprehensive and nuanced approach to screen time management, offering tailored responses based on user engagement.

Conflict of Interest

Author declares that they have no conflict of interest

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