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Blinkora: A Smart Digital Wellbeing App for Eye Health and Screen-Time Management

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Abstract

Screen time is among the major factors leading to the increasing cases of eye strain and other health problems in the world today. In this regard, there is the need to develop solutions to help address this problem. Hence, this research introduces Blinkora, an android-based smart system that helps to analyze and control excessive screen usage. The proposed system combines application usage analytics and face detection capabilities on-device for the effective tracking of user interaction. Using the built-in device camera, the system is capable of confirming the active participation of the user(s) on the screen. The Blinkora system uses Android Usage Stats APIs and simple image processing algorithms to perform application-level analytics and face detection respectively. Moreover, it calculates measures of exposure levels and addiction scores that measure dependency on screens. The entire process occurs on the device itself to achieve efficiency and guarantee privacy. Experiments conducted show that Blinkora efficiently merges the processes of monitoring, analyzing, and providing feedback to help increase user awareness. The presented method provides an effective solution that is both feasible and efficient for controlling screen usage and protecting one's eyes from harm.

Keywords: Screen Time Monitoring, Eye Health Analysis, Android Application, Face Detection, Usage Analytics, Digital Well-Being, Smart Alerts, Mobile Health.

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1. Introduction

The rapid evolution of the smartphone technology industry has revolutionized communication, learning, and entertainment. Nevertheless, the rapid development of this industry poses numerous health risks. Excessive use of smartphones has been linked with computer vision syndrome, characterized by eye discomfort, blurry vision, and headaches, among other problems that can have negative consequences on productivity [1]-[3].

It is essential to consider this issue and implement measures to monitor and mitigate the health risks posed by excessive smartphone usage. Currently existing apps aimed at measuring screen time tend to concentrate mostly on time spent using devices rather than on several more crucial components such as presence of a person using the device, the way of usage, and potential health risks associated with it [3], [4]. Furthermore, most systems take into account only one user, despite the possibility of several users using the same device at once [5].

In order to overcome such limitations, Blinkora, an intelligence-based Android application designed for analyzing the screen time and monitoring eye health, is proposed in this paper. Blinkora combines usage metrics with facial recognition features in order to track screen interactions and ensure the presence of the user. Using the captured face pictures, the system identifies the users of an Android application and calculates personal statistics on screen usage. Besides, Blinkora analyzes the continuous duration of using devices and applications in order to identify behavioral patterns. Additionally, Blinkora includes an alert system that sends notifications based on the set boundaries. This alerting feature includes not only visual notifications but also advice on how to protect eyes (e.g., eye exercises).

The Blinkora system design was done through Android Studio using the Kotlin language. Moreover, all the operations of the system are done on-device to guarantee low latency and higher data security. By incorporating user identification, real-time tracking, adaptive warnings, and use visualization, the Blinkora system provides a practical framework for encouraging digital wellness as well as mitigating the possible dangers of screen addiction. The rest of this paper is structured as follows: Section II gives a review of previous research on the topic of screen use tracking and digital wellness tools. Section III elaborates on the methodology behind the Blinkora system. Section IV discusses the results of this study.

2. Literature Survey

The rise of smartphone usage has caused increased studies on how constant exposure to digital screens affects humans' health. It has been established that the extensive use of digital screens leads to digital eye strain, resulting in such issues as dryness, blurred vision, headaches, and low productivity [1]-[4]. Young people are especially prone to developing those disorders because they constantly interact with their phones and other digital screens [3]. Moreover, the increased usage of digital screens during the COVID-19 pandemic has exacerbated the situation [5]. Health organizations, such as the World Health Organization, advise limiting screen exposure and engaging in physical activities in order to avoid adverse consequences [6]. Also, the scientists underline the need to measure and monitor screen time and develop prevention methods that will help decrease visual strain [7]. However, most of the existing tools for measuring digital well-being neglect this advice, concentrating solely on counting screen time [3], [4].

Machine learning and computer vision developments have led to the creation of intelligent surveillance systems. The deep learning model put forward by Ian Goodfellow et al. enhances the extraction of features and patterns [8], whereas the statistical pattern recognition technique suggested by Anil K. Jain et al. forms a robust base for classification operations [9]. Object detection algorithms in real-time such as YOLO designed by Joseph Redmon et al. facilitate effective object detection in varying settings [10]. Moreover, mobile sensing technology and smartphone imaging systems offer continuous surveillance through mobile phone sensors and cameras [11], [12]. Yet, these techniques usually demand significant computing capabilities, which makes them less feasible for real-time mobile surveillance applications [13], [14].

Screen time monitoring applications possess numerous limitations. In most cases, they assume a single user and fail to accommodate multiple users for accurate usage attribution in devices that may be used by more than one person at a time. Besides, they lack real-time exposure detection capability and personalized alerts based on the user's usage habits. These applications tend to use fixed threshold values, which do not necessarily match different usage patterns; hence, they become ineffective when it comes to health risk evaluation and generating alerts. Vision-based detection techniques tend to perform excellently in object detection applications but tend to be computationally expensive and not real-time adaptable [15]. In the same vein, deep learning methods tend to be expensive to implement owing to the large amount of data required and high processing capabilities [13], [14]. In addition, mobile sensing techniques are geared towards activity detection and monitoring without health risks evaluation [11].

The other major issue with the existing systems is the issue of privacy. Most of the techniques use cloud computing which leads to latency and potential threats related to data security. On-device computing is the more secure and efficient option but necessitates the use of optimized models that can run efficiently in real time. On the whole, present-day systems are constrained by lack of multi-user capability, adaptive thresholding, health-based alert mechanism, and private data protection measures. This reveals the importance of developing a smart, light, and real-time monitoring system. With its implementation of face detection on the device, continuous usage analysis, and adaptive health-based alerting, the Blinkora system fulfills all these requirements.

3. Proposed Methodology

The proposed Blinkora system is designed to monitor screen usage and detect user presence using face detection techniques, as illustrated in Fig. 1. This process starts when the app runs and monitors screen usage based on the Android UsageStats API. There is an assessment made concerning the predefined usage limit. In case there is still room left, the system continues monitoring screen usage. Once the limit is met, the front camera gets activated in order to take a picture of the user's face. Preprocessing activities include normalization, noise removal, and extraction of key facial features. Then the process of detecting faces takes place according to a predefined confidence value. If there is no face detected, the user is notified about that and further monitoring continues. However, in case there is a face detected, the system logs screen usage time, saves the taken picture of the user and updates the information about user's usage time. Then it calculates the overall time used for playing games in terms of hours and minutes and notifies the user about that. Moreover, it keeps track of all the face pictures taken and their associated usage time for each particular session.

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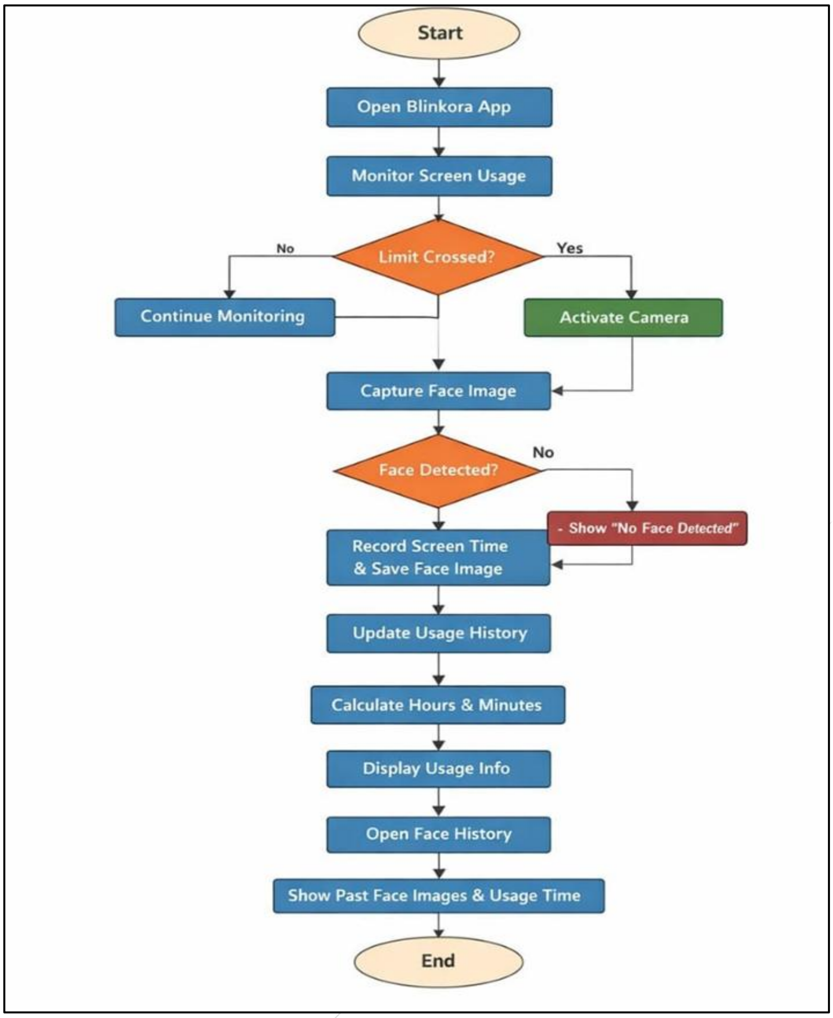

Figure 1. Proposed Work Flow

A. Face Detection Model

The Blinkora platform utilizes a pre-trained face detection model that has been optimized for mobile devices and operates completely on-device without requiring any training within the Blinkora platform. The model works on images taken by the front camera of the device when the user interacts with it. The image is first acquired, then undergoes several stages including resizing, normalization, and noise reduction. Noise reduction methods are used to get rid of any image distortion due to lighting, shadows, or motion blurring while retaining important information in the image. The next step is the segmentation process where the bounding box detection method is employed to segment the facial portion of the image. After this, facial landmarks are detected in a process called feature extraction to identify certain important parts of the face. Feature vector extraction provides important features of the face, which can be used to validate the presence of the face. The validation is done using confidence thresholding, whereby a face is said to have been detected if the confidence exceeds a predetermined threshold. This makes the process accurate and fast enough to detect users reliably. It should be noted that due to its size and pre-training on the side of the framework provider, it works efficiently on devices like mobile phones.

B. Classification and Screen Time Analysis

In the classification stage, the collected screen usage data is classified based on the predefined threshold values. The classification does not make use of any machine learning classification algorithms. The user's screen exposure level can be classified as:

- Low Usage: Less than 60 minutes
- Moderate Usage: Between 60 to 120 minutes
- High Usage: More than 120 minutes

The classification of user screen exposure level can be made to determine the level of digital exposure and the risk involved. An addiction score is also generated to determine the level of user addiction to screen usage.

$$Addiction\ Score\ = \left(\frac{Total\ Screen\ Time}{Recommended\ Limit}R\right)\times\ 100$$

For example, let's assume the user has spent 120 minutes in front of the screen, and the recommended limit is 60 minutes. In this case, the addiction score would be 200%.

C. Adaptive Alert Mechanism

An adaptive alarm system is activated depending on the screen time exposure classification. In case the user breaches a pre-set time period during the use of the screen, an alarm message is displayed with information on time spent, health risk levels, and eye exercise suggestions. When the user ignores the alarm, further alarms are set at progressively higher duration periods (such as 30 minutes and 45 minutes).

Algorithm

The working process of the Blinkora system can be expressed in the following algorithm:

Step 1: Start the application

Step 2: Initialize screen time monitoring by using the "UsageStats API"

Step 3: Continuously monitor screen time

Step 4: Compare screen time with the limit

Step 5: If screen time < limit

Continuously monitor screen time

Else

Enable the front camera

Step 6: Capture the image by using the front camera

Step 7: Perform face detection on the captured image

Step 8: If face detection == "yes"

Store the image in local storage

Record screen time

Update user history

Else

Discard the image

Step 9: Classify the level of screen time

Step 10: Generate an alert by using the screen time level

Step 11: Display screen time statistics and recommendations

Step 12: End

4. Results and Discussion

The Blinkora system was developed and tested using an Android system, enabling evaluation of its efficiency in real-time tracking of screen time and presence detection. In addition, the system combines the use of application statistics generated using the Android UsageStats API and facial recognition in order to track users' interactions accurately. The test results prove that the system can track screen interactions efficiently while confirming user presence with minimal delay since the process occurs locally.

As shown in Fig. 2, the system uses the authentication interface to provide a secured entry into the system using user identification details and personalizes their screen usage. On successfully logging into the system, the system supports multiple users through the profiling feature, as illustrated in Fig. 3, which categorizes users into either Owner, Friend, or Guest. This approach ensures accurate tracking of users' screen usage without duplication, especially in cases where the device is used by multiple users.

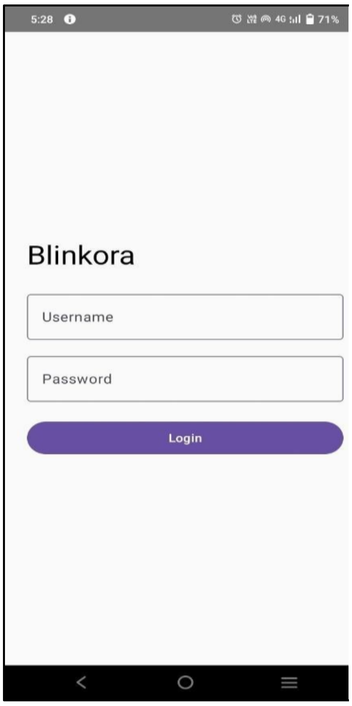

Figure 2. Blinkora User Login Interface

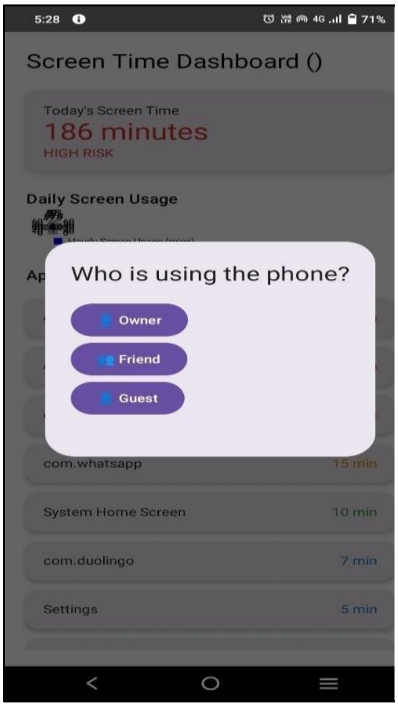

Figure 3. User Identification and Profile Selection Module

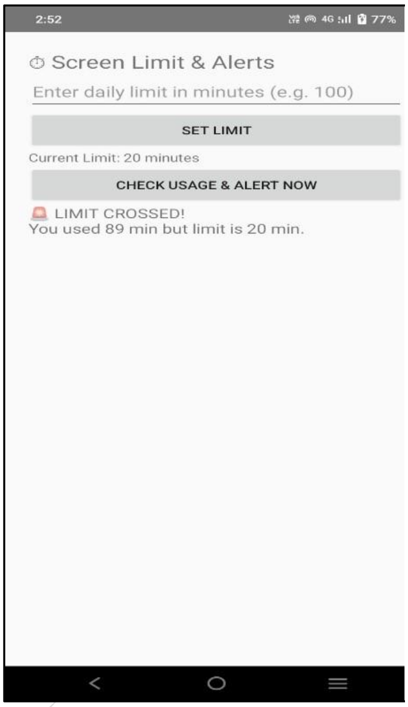

Figure 4. Screen Limit and Alerts

The screen monitoring and alarm system illustrated in Fig. 4 lets the user set the time threshold for screen use, and constantly checks whether the actual usage meets that threshold. Upon crossing the threshold, alerts would be issued and instant feedback provided. The screen monitoring system also offers manual checking of usage via “Check Usage & Alert Now” on the interface, providing users with timely information about their usage. Face capture system illustrated in Fig. 5 is a crucial component that validates the presence of the user during interactions with the device. Facial images captured by the front-facing camera will be processed locally, providing a high level of privacy and minimizing latency time.

The system offers usage analytics via dashboard visualization, as shown in Fig. 6. It gives screen usage statistics on an individual basis so that total screen usage time can be clearly identified. Moreover, the usage profile and weekly usage analytics, as presented in Fig. 7, reveal temporal screen usage trends so that peaks in usage can be easily detected. Usage level classification (low, medium, or high) and addiction calculation offer quantitative measures of screen usage. In addition, application-wise usage distribution reveals popular applications, helping users make informed decisions about controlling their screen time usage.

Figure 5. Face Capture Interface for User Identification

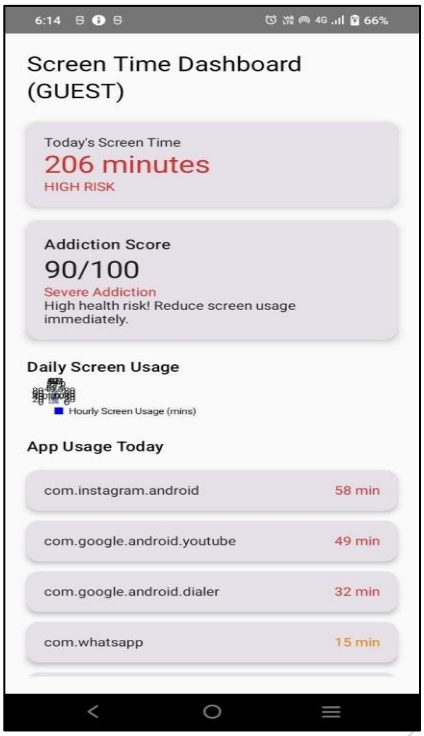

Figure 6. Screen Usage of Guest

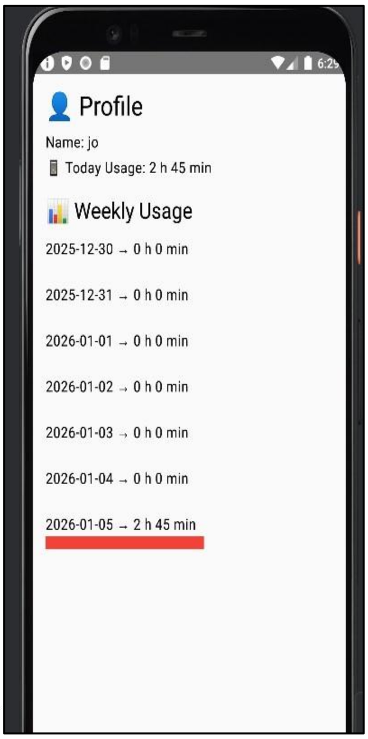

Figure 7. User Profile and Weekly Usage Analysis

The proposed system maintains a historical repository of usage data and associated face detection events, enabling retrospective analysis of user behavior. The integration of adaptive alerts and personalized recommendations, such as reminders for breaks and eye exercises, further enhances the system's capability to promote digital well-being. Overall, the results indicate that Blinkora delivers a reliable, efficient, and user-centric solution for monitoring screen exposure, improving awareness, and encouraging healthier usage patterns.

5. Conclusion

An intelligent Android-based application, "Blinkora" was developed to monitor screen time and promote digital well-being through real-time analytics and user presence detection. The system incorporates the usage analytics together with face detection functionality, making it possible to monitor the actual level of user engagement with the screen effectively. The developed system introduces several improvements to current screen time monitoring systems, including multi-user capabilities, adaptive monitoring techniques, and personalized feedback generation methods. The system allows for successful detection of excessive screen usage cases and provides users with valuable feedback by applying visual analytics, risk classification techniques, and recommendation mechanisms. On-device analytics allows the application to achieve low latency, high performance levels, and better user data privacy. Observations made during the experiment demonstrate that Blinkora is capable of monitoring user activities, supporting multiple users and generating useful feedback. Future research efforts could be aimed at cross-device synchronization capability introduction, implementation of predictive models based on machine learning algorithms, as well as integration with wearables. Improvement in adaptive alerts and health analytics could enhance the effectiveness of the developed solution.

References

[1] Likka, Melaku Haile, Samson Alemayehu, Dejene Hurissa, Betelhem Eshetu, Tesfaye Bayu, Tamirat Yenealem, Hanna Getachew et al. "Digital eye strain and associated factors among final-year undergraduate students in public universities in southern Ethiopia." Exploration of Digital Health Technologies 3 (2025): 101173.

[2] Beeson, Danielle, James S. Wolffsohn, Thameena Baigum, Talaal Qureshi, Serena Gohil, Rozia Wahid, and Amy L. Sheppard. "Digital eye strain symptoms worsen during prolonged digital tasks, associated with a reduction in productivity." Computers in Human Behavior Reports 16 (2024): 100489.

[3] Mataftsi, Asimina, Aikaterini K. Seliniotaki, Stella Moutzouri, Efthymia Prousali, Kianti R. Darusman, Adedayo O. Adio, Anna-Bettina Haidich, and Ken K. Nischal. "Digital eye strain in young screen users: A systematic review." Preventive Medicine 170 (2023): 107493.

[4] Mylona, Ioanna, Mikes N. Glynatsis, Georgios D. Floros, and Stylianos Kandarakis. "Spotlight on digital eye strain." Clinical Optometry (2023): 29-36.

[5] Alabdulkader, Balsam. "Effect of digital device use during COVID-19 on digital eye strain." Clinical and Experimental Optometry 104, no. 6 (2021): 698-704.

[6] World Health Organization. Guidelines on Physical Activity, Sedentary Behaviour and Sleep for Children Under 5 Years of Age. World Health Organization, 2019.

[7] Sheppard, Amy L., and James S. Wolffsohn. "Digital eye strain: prevalence, measurement and amelioration." BMJ open ophthalmology, (2018) 3, no. 1.

[8] Goodfellow, I., Bengio, Y., and Courville, A., Deep Learning, MIT Press, Massachusetts, USA, 2016. http://www.deeplearningbook.org

[9] Jain, Anil K., Robert P. W. Duin, and Jianchang Mao. "Statistical pattern recognition: A review." IEEE Transactions on pattern analysis and machine intelligence 22, no. 1 (2000): 4-37.

[10] Redmon, Joseph, Santosh Divvala, Ross Girshick, and Ali Farhadi. "You only look once: Unified, real-time object detection." In Proceedings of the IEEE conference on computer vision and pattern recognition, (2016): 779-788.

[11] Lane, Nicholas D., Emiliano Miluzzo, Hong Lu, Daniel Peebles, Tanzeem Choudhury, and Andrew T. Campbell. "A survey of mobile phone sensing." IEEE Communications magazine 48, no. 9 (2010): 140-150.

[12] Hunt, Brady, Alberto J. Ruiz, and Brian W. Pogue. "Smartphone-based imaging systems for medical applications: a critical review." Journal of Biomedical Optics 26, no. 4 (2021): 040902-040902.

[13] Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." 2014 arXiv preprint arXiv:1409.1556.

[14] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." Advances in neural information processing systems 2012, 25.

[15] Sivaraman, Sayanan, and Mohan Manubhai Trivedi. "Looking at vehicles on the road: A survey of vision-based vehicle detection, tracking, and behavior analysis." IEEE transactions on intelligent transportation systems 14, no. 4 (2013): 1773-1795.Journal of Selected Topics in Applied Earth Observations and Remote Sensing 18 (18): 2151–1535.