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A MACHINE LEARNING APPROACH TO EYE BLINK DETECTION IN LOW-LIGHT VIDEOS

Muhammad Furqan Rasyid*[1], Muhammad Rizal[2], Wilem Musu[3], Muhammad Sabirin Hadis[4]

[1]Department of Informatics Management, Dipa Makassar University, Indonesia
[2,3]Department of Informatics Engineering, Dipa Makassar University, Indonesia
[4]Department of Electrical Engineering and Computer Science, Kanazawa University, Kanazawa, Japan
Email: [1]muhammad.furqan@undipa.ac.id, [2]muhammad.rizal@undipa.ac.id, [3]wilem.musu@undipa.ac.id, [4]sabirinhadis@stu.kanazawa-u.ac.jp

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Abstract

Inadequate lighting conditions can harm the accuracy of blink detection systems, which play a crucial role in fatigue detection technology, transportation and security applications. While some video capture devices are now equipped with flashlight technology to enhance lighting, users occasionally need to remember to activate this feature, resulting in slightly darker videos. Consequently, there is a pressing need to improve the performance of blink detection systems to detect eye accurately blinks in low light videos. This research proposes developing a machine learning-based blink detection system to see flashes in low-light videos. The Confusion matrix was conducted to evaluate the effectiveness of the proposed blink detection system. These tests involved 31 videos ranging from 5 to 10 seconds in duration. Involving male and female test subjects aged between 20 and 22. The accuracy of the proposed blink detection system was measured using the confusion matrix method. The results indicate that by leveraging a machine learning approach, the blink detection system achieved a remarkable accuracy of 100% in detecting blinks within low-light videos. However, this research necessitates further development to account for more complex and diverse real-life situations. Future studies could focus on developing more sophisticated algorithms and expanding the test subjects to improve the performance of the blink detection system in low light conditions. Such advancements would contribute to the practical application of the system in a broader range of scenarios, ultimately enhancing its effectiveness in fatigue detection technology.

Keywords: *confusion matrix, eye blink detection, flashlight, low-light video, machine learning.*

1. INTRODUCTION

In today's digital era, video has become one of the most popular and widely used media in various fields, such as industry, entertainment, and research [1]. Video is also often used in medical testing to see the patient's condition. However, the main problem with video analysis is that some videos still have qualities that complicate the data analysis process. Many tasks can be accomplished with video [2]. One of these videos is detecting the blink of an eye in a subject, which can provide important information in medical research and diagnosis. Catching eye blinks in low-light videos is difficult because many factors, such as video quality, lighting, camera position, and subject movement, can affect the analysis results. Therefore, it requires a proper and sophisticated approach to solve the problem.

Several previous studies detect eyes blinking. Research conducted by [3] notices eyes blinking using the EAR (Eyes Aspect Ratio) method with an accuracy of up to 97%. The study by [4] introduces a new unsupervised learning algorithm that combines thresholding and a mixed Gaussian model (GMM) to achieve precise and effective eye blink detection. The proposed algorithm outperforms other recent methods regarding detection precision and F1 score. Research by [5] used smoothed nonlinear energy operator (SNEO) and variational mode extraction (VME) to detect epileptiform discharge in frontal leads. This technique is used to catch eye blinks.

Machine learning techniques are one of the most effective approaches to detecting eye blinks in videos. Machine Learning (ML) is a technology in which machines are trained independently without human direction [6]. Machine learning is artificial intelligence that allows computers to learn without being explicitly programmed [7]. Machine learning algorithms are trained on data and learn to identify patterns in the data [8]. There are four types of machine learning algorithms: supervised, unsupervised, semi-supervised, and reinforcement learning [9]. The machine learning approach has opened up new possibilities for detecting eye blinks in videos with high accuracy.

In recent years, the machine learning approach has become very popular in video analysis and a centre of research attention in the computer field. Such as for analyzing buyers' shopping goals in online shops [10], predicting the spread of Covid-19

[11], and its use in the medical world [12]. In the meantime, research using machine learning has been carried out a lot to detect eye blinking. The study by [13] introduces a new model by combining a Convolutional Neural Network (CNN) and a Support Vector Machine (SVM). This study obtained an accuracy of 97.44% for the eyes status classification task on the CeW dataset and an F1 score of 92.63%. Research by [14] determines the degree of open and closed eyes. This research offers a real-time blink detection method using machine learning technology and computer vision libraries. The proposed method obtains high accuracy to indicate whether the look is open or closed.

This research will discuss a machine-learning approach to detect eye blinks in low-light videos. Videos with poor image quality or low resolution are referred to as low-quality videos, which can be caused by various factors such as limitations of the device used to record or process the video, unsupported environmental conditions, or poor data transfer when uploading or watching videos online. The viewing experience can be compromised if essential details are challenging to see or the sound is difficult to hear in minimally-lit videos. Still, some types of videos, such as surveillance videos or videos taken in minimally-lit conditions, may only sometimes be of high quality. The proposed system builds on a library. Machine learning-based Python, namely media pipe. MediaPipe is an open-source framework from Google used to build applications that focus on processing visual data, such as facial recognition, pose detection, hand tracking, etc. This framework was developed using machine learning [15], enabling developers to build machine learning models and image processing algorithms quickly and efficiently, supporting various hardware and operating systems.

In detecting eye blinks in low-light videos, machine learning is used to identify eye-blinking patterns. In this case, the media pipe library creates facial landmarks. Facial landmarks are the critical points on a person's face, such as the corners of the eyes, nose, and lips. Mediapipe can provide good enough accuracy to recognize eye blinks in videos with a high degree of accuracy. Compared to other landmark methods, the machine learning approach to detect eye blinks obtains relatively good accuracy, but some challenges must be overcome. Therefore, this paper discusses using a machine-learning process to detect eye blinks in low-light videos. Apart from that, We will also discuss some of the challenges and how to overcome them. Finally, this research will evaluate the results of the machine learning approaches we have discussed and provide recommendations for future development of these techniques. This paper will better understand machine learning approaches to detect flicker in low-light videos. It can contribute an important role in video analysis and medical technology development.

2. RESEARCH METHOD

The proposed system handles eye condition classification, and eyes blink detection tasks in minimally-lit videos. Video is one of the technologies that exist today. The modern world is greatly influenced by existing technology [16]. The proposed method in this research used is shown in Figure 1.

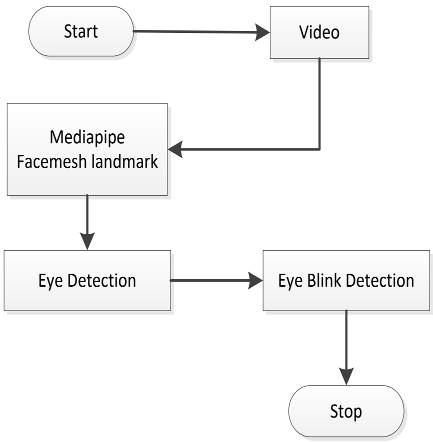

Figure 1. Proposed method

The inputs in this task do not necessarily display a temporal or sequential relationship; for each piece of information, one output is expected. On the other hand, blink detection is the job of detecting blinks in a particular video in a sequence of frames. Since the input to this task is video, the edges are sequentially related. A list of blinks that occur is expected as output for each video input. Blink is defined as a sequential sequence of frames with eyes closed and then open. In this way, the blinks will be represented by their corresponding sequence boundaries. In this work, we treat the eye blink detection task as an extension of the eye state classification task. Overall, an explanation of the proposed method will be discussed below.

2.1. Video

Video is a form of visual recording that can display moving images and sound. In the system created, video format files are used as input data. The data collected is facial videos with minimal lighting. Unlike the low resolution [17], the input video has minimal lighting. Figure 2 shows a snippet of the image used as input for the system being created.

Figure 2. Data input

Video is a form of visual recording that can display moving images and sound. In the system created, video format files are used as input data. The data collected is facial videos with minimal lighting. Unlike the low resolution [17], the input video has minimal lighting. Figure 2 shows a snippet of the image used as input for the system being created.

Although some cameras have built-in flashlights, some users must remember to turn them on, resulting in blurry videos due to a lack of light when recording. The flashlight is a portable lighting device that usually consists of a small lamp and a battery operated with an on/off switch. This tool is also known as a flashlight or small torch and is generally used to illuminate areas or objects that are poorly lit or in dark conditions. Figure 3 shows the difference between images taken with good and low-lighting.

A B

Figure 3. A. Good light; B. Low-light

2.2. Mediapipe face landmark

Mediapipe is a software development kit utilized for constructing machine learning models that can analyze time-based data, including but not limited to videos, audio, and more. Furthermore, the Mediapipe Facemesh Landmark is a model of the media pipe designed to detect and track landmarks or human facial features in real-time images or videos. Face mesh models use deep learning technology to recognize landmarks or facial features, such as the dots on the lips, nose, eyebrows, and other facial features. As is known, deep learning is a subset of Machine learning that utilizes or employs something of artificial neural networks to replicate the way the human brain learns and processes information [18].

This model can be used in various applications, such as facial animation, emotion recognition, and augmented reality. Face mesh produces output in the form of 3D landmark coordinates on the front, which can be used to draw a three-dimensional mesh or network on the face's surface. This facial landmark information can be used to develop applications such as facial recognition, measurement of facial features, and control of games or applications that use facial movements as input.

Mediapipe Facemesh Landmark can be easily integrated into larger applications or systems using APIs and SDKs provided by Google. This model was developed using TensorFlow so it can be retrained or adapted to user needs. This model works as long as the frequency of the video data at the same time some landmark points produce a frequency with a higher deviation than the actual accelerometer frequency[19]. Figure 4 shows the process of marking facial landmarks using the Mediapipe library.

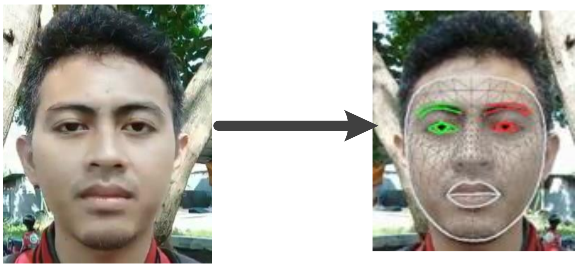

Figure 4. Face-landmark using mediapipe

2.3. Eyes detection

Eye detection is an image processing and computer technology that aims to identify and locate the eyes in digital images or videos. This technology has broad applications, including security surveillance, biometrics, augmented reality, and emotion recognition. The eye detection process uses image processing algorithms to identify eye features such as the iris, pupil, and conjunctiva. Information about the position, size, and orientation of the eyes in the image or video is then extracted from the image data. Eye recognition is becoming very important in some applications, such as emotion recognition, where eye detection can be used to measure changes in facial expressions. This technology also has an essential role in security surveillance and biometrics, where eye detection can be part of facial recognition and identity verification systems. Figure 5 displays the human eye.

Figure 5. Human’s eye

Many methods are used for eye detection [20], such as involving various image processing techniques, including edge detection, image segmentation, and pattern recognition. Different deep learning approaches have been implemented to improve the speed and accuracy of identifying eyes, such as using convolutional neural networks (CNNs). Mediapipe made a system to detect the eye. Figure 6 shows the system created to see eye blinks.

Figure 6. Eye landmark

2.4. Eyes Blink Detection

Eye blink detection or eye blink detection is a technology used to recognize and detect eye movements, wildly blinking movements. This technology is often used in applications that require analysis of emotions, states of concentration, or fatigue monitoring. The process of eye blink detection involves the use of algorithms and image processing techniques to recognize changes in the shape and position of the eyes. The image data is then analyzed to calculate the number of flashes and the time interval between seconds. Eye blink detection can be applied in various fields, including psychology, sports, application development, and security. In psychology, this technology can help identify signs of fatigue or cognitive impairment in individuals, while in sports, this technology can be used to monitor athletes' concentration and fatigue levels. In application development, eye blink detection is used to build applications that respond to eye movements, such as applications that allow users to control devices using eye movements. In security, eye blink detection can be used as an authentication factor in facial recognition and user identification systems.

Once the landmarks in the eye are found, the next task in the system will be to differentiate the Landmark colours. The landmark point will be yellow when the eyes are open and turn green when the eyes are closed. Both conditions are shown in Figure 7.

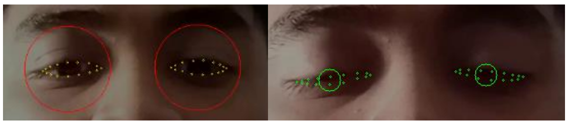

Figure 7. Eyes Blink Detection

3. RESULT

The data used for testing is a video that has lowered the saturation level by 20% from the original video. To reduce saturation, we use an artificial intelligence-based website. This website is widely used to adjust the video saturation level. Figure 8 illustrates the video conversion process utilizing that technology.

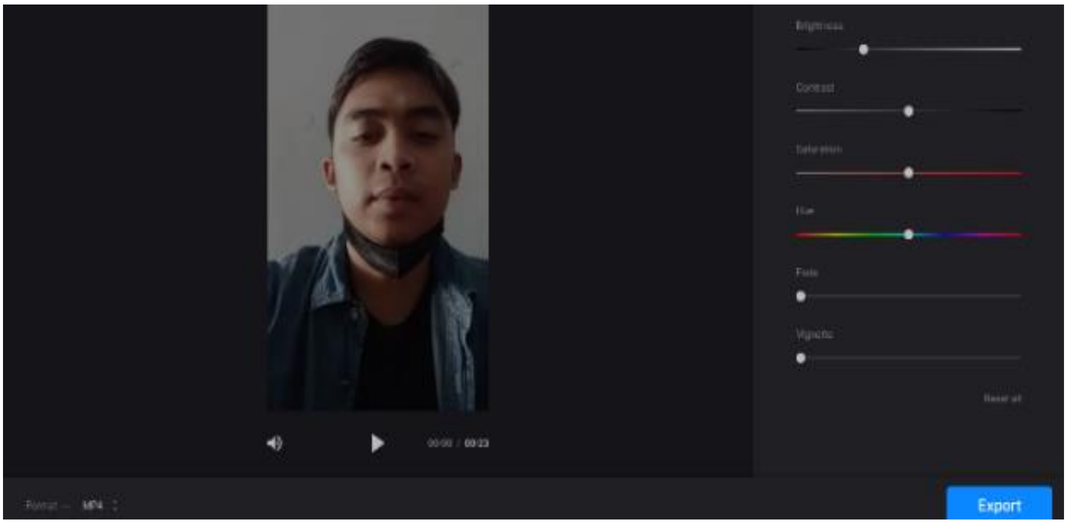

Figure 8. Use of AI-based websites to reduce saturation levels

Saturation in a video refers to the intensity of the colors in the video. A video with high saturation will have bright and vibrant colors, while a video with low saturation will have muted and washed-out colors. Saturation can be adjusted using various video editing tools, and it can be used to create multiple effects. For example, increasing saturation can make a video more visually appealing, while decreasing saturation can create a more somber or dramatic mood.

Saturation and brightness are related in that they both affect the overall appearance of a color. A highly saturated color of the same hue will appear brighter than a low-saturated color. Conversely, a dark color will appear less saturated than a light color of the same shade. The relationship between saturation and brightness can create various effects in images and videos.

Tests on the system created were carried out to determine the system's accuracy for detecting the human eye in minimally-lit videos. This test uses 31 videos that last 5-10 seconds. Video objects consist of men and women between 20 and 22. Testing is a process for evaluating the quality or performance of a system. In addition, testing also aims to find and correct errors or problems before the product or system is realized. Different approaches can be utilized for testing, including examination, experimentation, or assessment, to establish whether the product or system conforms to the predetermined requirements. Figure 9 shows some examples of test data.

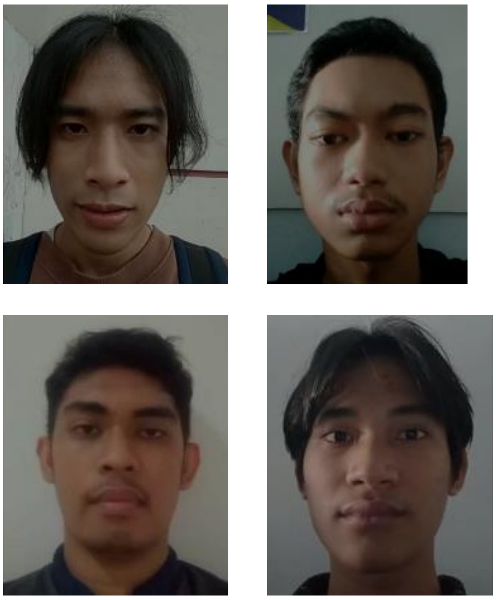

Figure 9. Data test

The test is carried out using the confusion matrix method to calculate accuracy. A confusion matrix is an accuracy measurement method usually used to solve classification problems and can be applied to binary classification for multiclass classification problems [21]. In addition to solving problems, confusion matrices are commonly used to summarize work related to category, a fundamental problem in many fields, such as applied mathematics, geostatistics, data mining, text analytics, finance, biomedicine, and biotechnology [22] [23]. Use this method to determine what percentage is obtained from the system [24]. The calculation of accuracy with the confusion matrix method is shown in Equation 1.

$$Accuracy = \left(\frac{TP+TN}{TP+FP+FN+TN}\right) x\ 100\% \qquad (1)$$

TP parameter represents true positive, FP represents false positive, TN represents true negative, and FN represents false negative [25]. An explanation of TP, TN, FP, and FN is presented in Table 1.

Table 1. Descriptions

Letter	Description
P	Prediction Class
A	Actual class
M	Eyes blink
N	The eye does not blink
TP	Predicted positive, and it was true
TN	Predicted negative, and it was true
FN	Predicted negative, and it was wrong
FP	Predicted positive, and it was wrong

The description table above explains that the rows represent actual class results, and the columns represent predicted class results [26]. The proposed system confusion matrix is presented in Table 2.

Table 2. Confusion matrix for eye blink detection system

pA	M	N
M	31 (TP)	0 (FN)
N	0 (FP)	0 (TN)

$$Accuracy = \left(\frac{31+0}{31+0+0+0}\right) x\ 100\%$$

$$Accuracy = \left(\frac{31}{31}\right) x\ 100\%$$

$$Accuracy = 100\ \%$$

The accuracy of the test is greatly influenced by the type of data chosen to be tested [27]. By leveraging a machine learning approach to detect eye blinks in minimally-lit videos, we have developed a predictive model that can recognize eye blinks accurately.

Our machine-learning approach can detect eye blinks in low-light videos with high accuracy. The model we developed achieves a perfect accuracy of 100%. These results indicate that the machine learning approach we have developed can effectively address the problem of poor video lighting for detecting blinks.

4. DISCUSSION

The test results show our model can recognize eye blinks in minimally-lit videos with high accuracy. The confusion matrix method is used to obtain the accuracy of the system created. Testing shows excellent results that are 100%. These results show that the machine learning approach we have developed can overcome the problem of low lighting in videos and provide more accurate and efficient results in detecting eye blinks.

The results are also compared with several other machine-learning techniques that have been applied to video analysis and have been reported in the literature. The results of the tests that have been carried out show that our machine-learning method can efficiently solve the problem of flicker detection in minimally-lit videos. The comparison results are presented in Table 3.

Table 3.Comparison with another method

Method	Accuracy
Eyes aspect ratio[3]	96.85%
Measurement vertical and horizontal at part of eyes [28]	90%
Facelandmark and u-LBPH[29]	95.5%
SNEO and VME[5]	95.04%
ML for eyes blink detection in low-light videos (proposed)	100%

The table shows the results of comparing five different methods for eye blink detection. The methods were evaluated on a dataset of videos of people blinking in various lighting conditions. The results show that the proposed method, which uses machine learning to detect eye-winking in low-light videos, is the most accurate method, with an accuracy of 100%. The other techniques have accuracies ranging from 90% to 96.85%.

The proposed method detects eye blinks by looking for changes in the shape of the eyes. The machine learning algorithm is trained to recognize these physical changes and classify them as blinks. The algorithm can detect blinks even in low-light conditions, which is challenging for other methods.

This study suggests that the proposed method is a promising new technique for eye blink detection.

Here are some additional details about each of the methods:

a. Eye aspect ratio (EAR): This method measures the balance of the eye's width to its height. When the eyes blink, the EAR decreases. This method is simple to implement and can be effective in well-lit conditions. However, it can be less accurate in low-light conditions.
b. Measurement of vertical and horizontal parts of the eyes: This method measures the distance between the top and bottom of the look and the left and right sides of the eye. When the eyes blink, the distance between the top and bottom of the eye decreases. This method is also simple to implement and effective in well-lit conditions. However, it can be less accurate in low-light conditions.
c. Face landmark and u-LBPH: This method uses facial landmarks and a uniform local binary pattern histogram to detect eye blinks. Facial landmarks are points on the face that are used to track the movement of the face. A uniform local binary pattern histogram is a feature descriptor that can be used to identify objects in images. This method is more accurate than the EAR and measurement of vertical and horizontal parts of the eyes, but it is also more complex to implement.
d. SNEO and VME: This method uses a spatial-temporal energy operator and a visual motion energy operator to detect eye blinks. The spatial-temporal energy operator is a feature descriptor that can be used to identify objects in videos. The visual motion energy operator is a feature descriptor that can be used to track the movement of objects in videos. This method is more accurate than the EAR, measurement of vertical and horizontal at part of eyes, and face landmark and u-LBPH methods, but it is also more complex to implement.

The proposed method is a promising new approach for eye blink detection. It is accurate, robust, and can be used in various lighting conditions.

Various essential applications can be developed from this eye detection system in health, security, and others. Specifically for medical purposes, this application can analyze a person's stress level. Changes in stress indicators can be influenced by the level of care activities [30].

Some limitations to this research need to be considered. First, the dataset we use may be representative of only some of the different types of video that might be found in real-world applications. Second, we use a machine learning library, namely Mediapipe. While this library has proven successful in many applications, machine learning methods such as Decision Trees and Support Vector Machines (SVM) can also be used in video analysis. Therefore, future research may consider other machine learning techniques to compare their performance with the machine learning approach we developed. In addition, future research can also consider environmental factors such as lighting and camera position in video analysis to improve model performance.

The proposed method could improve driver safety by detecting when drivers are fatigued. Drowsy driving is a significant factor in accidents, and the proposed method could be used to warn drivers when they are at risk of falling asleep at the wheel. The proposed method could also be utilized for developing new healthcare applications, such as detecting eye diseases or monitoring treatment progress.

Here are some additional details about how the proposed method could be used to improve driver safety and to develop new healthcare applications:

a. Driver safety: The proposed method could detect drowsy driving by tracking the frequency of eye blinks. Drivers who flash less often are more likely to be fatigued. The proposed method could alert drivers when they are at risk of falling asleep and recommend that they take a break from driving.
b. Healthcare applications: The proposed method could be used to detect eye diseases, such as dry eyes and glaucoma. Dry eye is a prevalent condition that can cause discomfort and vision issues, while glaucoma is a severe eye disorder that can harm the optic nerve and lead to vision loss. The proposed method could detect these diseases early on when they are easier to treat.

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