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# USING THE HUMAN FACE RECOGNITION METHOD BASED ON THE MOBILENETV2 NEURAL NETWORK IN AUTHENTICATION SYSTEMS

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## ABSTRACT

The rapid development of biometric authentication systems has led to the widespread adoption of face recognition technologies. This study explores the application of the MobileNetV2-based neural network for human face recognition in authentication systems. The advantages of MobileNetV2, such as its lightweight architecture and high computational efficiency, make it a suitable choice for real-time authentication on edge devices. The proposed method enhances recognition accuracy while maintaining fast processing speeds, ensuring a balance between security and performance. Experimental results demonstrate the effectiveness of the approach under varying lighting conditions and different angles of facial orientation. The study also discusses potential challenges, including spoofing attacks and dataset limitations, and proposes solutions to improve robustness. The findings contribute to the advancement of secure and efficient biometric authentication systems.

**Keywords:** Face Recognition, MobileNetV2, Biometric Authentication, Neural Networks, Security Systems, Real-time Processing, Deep Learning, Identity Verification.

## INTRODUCTION

The modern development of computer vision and artificial intelligence has led to significant progress in methods of automatic recognition of human faces, which is widely used in the fields of security, biometric identification, access control, entertainment services and even marketing [1]-[10]. And here different methods and approaches can be used [11]-[36]. Despite the rapid development of technology, existing face recognition algorithms face a number of problems, including low accuracy in difficult lighting conditions, limited performance on mobile devices and limited capabilities of generalizing models for recognizing different types of faces. One of the promising approaches to solving these problems is the use of deep neural networks, in particular compact architectures that can provide high efficiency at low computational costs. The MobileNetV2 neural network is one of the most optimal models for mobile platforms and devices with limited resources due to its efficient structure combining inverted residual blocks and deep convolutional layers. [37]-[45] It allows to reduce the number of parameters and maintain high recognition accuracy, which makes it attractive for implementation in real conditions. However, even the use of MobileNetV2 in face recognition tasks requires further improvement, in particular, adaptation to new data sets, optimization for specific application scenarios and the use of additional methods to increase accuracy. One of the promising areas of improvement is the use of pre-training methods, fine-tuning the network on specialized samples, as well as the use of additional layers or mechanisms for post-processing the classification results.

Of considerable interest is also the problem of real-time face recognition, when the system must provide not only high accuracy, but also image processing speed. This is especially relevant in the conditions of streaming video surveillance, integration with mobile applications and intelligent access systems. In such cases, classic deep neural networks can be too cumbersome, while MobileNetV2, provided that appropriate optimization is provided, provides a balance between speed and accuracy. An additional challenge is to increase the algorithm's resistance to changes in the face

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position, lighting variations, the presence of accessories and other factors that can affect the quality of recognition.

Therefore, improving the face recognition method based on the MobileNetV2 neural network is a relevant task that has significant scientific and practical interest. The research is aimed at developing methods to increase the accuracy and speed of the model, as well as its adaptation to difficult operating conditions. The results of the work can be used in security systems, access control, business process automation, personalized services and other industries where effective face identification in real time is required.

## LITERATURE REVIEW

Currently, many researchers are working on the problem of face recognition. To solve it, they use completely different methods. Let's consider several such works.

Let us begin with the article [46] as it is a complete review about this theme. There authors highlighted major applications, challenges and trends of face recognition systems in social and scientific domains. Moreover, they discuss some key challenges such as variability in illumination, pose, aging, cosmetics, scale, occlusion, and background. Along with classical face recognition techniques, most recent research directions are deeply investigated, i.e., deep learning, sparse models and fuzzy set theory.

Srivastava, G., & Bag, S. in [47] note that the domains of neuro-marketing and face recognition marketing remain understudied. Neuro-marketing and facial recognition marketing are artificial intelligence-enabled marketing techniques that assist in gaining cognitive insights into human behavior.

Researchers in [48] present a comprehensive review about the recent advance of each element of the end-to-end deep face recognition, since the thriving deep learning techniques have greatly improved their capability of them.

The paper [49] introduces another aspect of adaptiveness in the loss function, namely the image quality. We argue that the strategy to emphasize misclassified samples should be adjusted according to their image quality. There is proposed a new loss function that emphasizes samples of different difficulties based on their image quality. This method achieves this in the form of an adaptive margin function by approximating the image quality with feature norms.

In [50] there is proposed MagFace, a category of losses that learn a universal feature embedding whose magnitude before normalization can measure with the quality of the given face. Under the new loss, it can be proven that the magnitude of the feature embedding monotonically increases if the subject is more likely to be recognized. In addition, MagFace introduces an adaptive mechanism to learn a well-structured within-class feature distributions by pushing easy samples to class centers while pushing hard samples away.

Qiu, H., and co-authors in [51] use synthetic face images, i.e., SynFace trying to solve the next problem: existing face recognition datasets are usually collected from web images, lacking detailed annotations on attributes (e.g., pose and expression), so the influences of different attributes on face recognition have been poorly investigated.

Further in this article we will consider our method for solving the problem of face recognition.

## THE HUMAN FACE RECOGNITION METHOD BASED ON THE MOBILENETV2 NEURAL NETWORK MATHEMATICAL DESCRIPTION

Let $I(x, y)$ – is a face image function where $x$ and $y$ – are the spatial coordinates of the image pixels. The image undergoes pre-processing, such as normalization (reducing to the range of values [0, 1]) and scaling to a standard size, such as 224 x 224 pixels.

MobileNetV2 uses a deep convolutional neural network architecture with narrow blocks, called “inverted residual blocks”, to extract key features. From a mathematical point of view, each block consists of the following operations:

– Depthwise Convolution is used to effectively reduce the number of calculations and parameters in convolutional neural networks. It consists of applying a separate filter to each channel of the input image instead of traditional convolution, which processes all channels simultaneously. This allows for a significant reduction in computational complexity, as the number of operations is reduced by dividing the convolution process into two separate phases: first a group convolution for each channel, and then a point convolution to combine information from different channels. This architecture allows us to preserve important spatial features from each channel separately, while improving the overall performance of the model. Group convolution is a key component for lightweight models such as MobileNet, where it is important to maintain a balance between speed and accuracy:

$$F(x,y) = W_d * I(x,y), \tag{1}$$

$F(x,y)$ – is the output after applying group convolution to the input image. This is a feature map that displays the spatial features of the image after processing with convolutional filters. The $x$ and $y$ coordinates indicate the positions of pixels in the output feature map;

$W_d$ – is a kernel or filter of the group convolution (Depthwise Convolution Kernel). It is responsible for processing each individual channel of the input image. It is important that a separate filter is applied for each channel, i.e. the number of filters corresponds to the number of channels of the input image;

$I(x,y)$ – is the input image or input tensor that contains information about pixels at positions x and y for each channel. From this tensor, features are taken that will be processed by group convolution filters.

In the context of group convolution, is the input image or input tensor that contains information about pixels at positions x and y for each channel. From this tensor, features are taken that will be processed by group convolution filters.

In the context of group convolution, $W_d$ is applied to each channel separately, i.e., unlike traditional convolution, where all channels are simultaneously processed by one filter, here the operation is performed independently for each input data channel;

– Pointwise Convolution is used to change the number of channels in a tensor without changing its spatial dimensions. Its main function is to combine information from different channels of the input tensor by applying a 1x1 filter. Pointwise Convolution allows you to combine features obtained from different channels after applying group convolution and integrate them in a more compressed form. It plays an important role in building efficient deep learning models, such as MobileNet, by reducing computational costs and the number of neural network parameters while maintaining high quality feature analysis:

$$F_{pw}(x,y) = W_p * F(x,y), \tag{2}$$

$F_{pw}(x,y)$ – result of the pointwise convolution operation at a point with coordinates $x, y$. This is the output tensor in which the number of channels changes, but the spatial dimensions remains the same.

$W_p$ – a set of 1x1 filters responsible for transforming the input channels. For each channel of the output tensor there is a separate filter $W_p$. The filters define the weights used to weight the channel values in the input tensor.

$F(x,y)$ – input feature tensor at point $x, y$, which is fed to the point convolution operation. This tensor contains a set of channels obtained after applying group convolution or previous layers of the network.

In general, point convolution combines information from all channels of the input tensor, changing the number of channels without changing the spatial dimensions.

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After each block, a nonlinear transformation is performed through an activation function, for example, ReLU6. The activation function ReLU6 (Rectified Linear Unit 6) is a variation of the classic ReLU function, which limits the output value between 0 and 6. Its mathematical expression looks like this:

$$ReLU6(x) = \min(\max(0, x), 6). \tag{3}$$

This means the following:
– if the input value *x* is less than or equal to 0, the output is 0 (as in standard ReLU);
– if the input value *x* is greater than 6, the output is capped at 6;
– if *x* is between 0 and 6, the output is *x* itself.
Then, for our case:

$$F_{out}(x, y) = \max\left(0, \min\left(F_{pw}(x, y), 6\right)\right), \tag{4}$$

$F_{out}(x, y)$ – is the result of a nonlinear transformation, i.e. the output of the ReLU6 activation function for each pixel or data element with coordinates *x,y*. The output value is limited between 0 and 6;

$\mathrm{F_{pw}(x, y)}$ – Pointwise Convolution result for each *x,y* coordinate pair. This is the intermediate result after applying the convolution, which is then passed through the ReLU6 activation function;

$\max(0, \ldots)$ – this part of the function is responsible for the fact that the output value cannot be less than 0. If $\mathrm{F_{pw}(x, y)}$ is less than 0, the result will be 0, i.e. negative values are truncated, which is part of the standard function ReLU;

$\min(\ldots, 6)$ – this part limits the maximum output value to level 6. If the value $\mathrm{F_{pw}(x, y)}$ is greater than 6, then the result of the function is limited to the number 6. This is a specific property of ReLU6, which prevents too large values, which can negatively affect the stability of the network.

Expression (4) allows:

– cutting off negative values through max(0,…), prevents negative activations from passing further through the network;

– limiting activations from above to 6 through min(…,6) helps maintain stability of calculations, reducing the probability of activation oversaturation, which is especially important for mobile devices and embedded systems.

Thus, expression (4) determines the activation for each data element, limiting the output within [0, 6] for stable and efficient operation of the neural network. Thanks to such processing, the model receives a set of features (Feature Map) representing key facial features.

The next step is to determine key points (Keypoint Detection) on the human face.

Each point can be described by coordinates $\mathrm{(x_i, y_i)}$, where i corresponds to the point number (e.g., left eye, right eye, nose, etc.). If $\mathrm{P = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}}$ is a set of key points, then the model should learn to predict these coordinates based on the received features:

$$P = f(P_{out}), \tag{5}$$

*P* – are the coordinates of key points (e.g. eyes, nose, mouth, etc.) on the face or any other important features that the model should predict. This is the final output that the neural network generates after training. Typically, these are coordinates in 2D space, expressed as a pair *(x,y)* for each key point;

$f$ – is a function that represents the prediction process. It can be part of a neural network that uses various nonlinear transformations, convolutions, or fully connected layers to determine the coordinates of key points based on the received features. The function f is responsible for processing the features and forming accurate predictions;

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$P_{out}$ – are features (Feature Map or outputs of previous layers of the neural network) obtained after passing the image or data through convolutional or other layers of the model. They contain generalized information about the object in the image (in our case, a face), on the basis of which the prediction is made. These features describe the structure, textures, contours, and based on them the model builds a prediction of coordinates.

The model, represented by expression (5), must learn to predict the coordinates of key points (P) based on the features describing the object ($P_{out}$). This approach allows you to effectively use the information obtained from the image to determine the exact location of important points (for example, facial features) for further identification or face recognition in automated control systems.

Having received the coordinates of the key points of the face, the system can compare them with previously stored templates or go through the next stage of classification. When using MobileNetV2 for human classification, a fully connected layer is added:

$$\hat{y} = softmax(W_c \cdot F_{out} + b_c), \qquad (6)$$

$\hat{y}$ – is the predicted output of the model, i.e. the probability that the input data belongs to a certain class. In the case of human classification, this can be different classes, for example, specific individuals. The vector y contains the probabilities for each possible class, and the sum of all these probabilities is 1 due to the softmax function;

softmax – is an activation function that converts a linear combination of features (the result of $\mathrm{W_c \cdot F_{out} + b_c}$) into probabilities that can be interpreted as belonging to each class. The softmax function normalizes these values so that they lie in the interval from 0 to 1, and the sum of the probabilities over all classes is equal to 1;

$\mathrm{W_c}$ – is the weight matrix of the fully connected layer, containing the coefficients that are applied to the features ($\mathrm{F_{out}}$) to obtain the final results before classification. Each row in the matrix W corresponds to a separate class, and this parameter is learned during model training;

$\mathrm{F_{out}}$ – is the output of features obtained from previous layers of the model. These features are generalized information that contains important characteristics of the object, in particular the face. Based on these features, the fully connected layer performs classification;

$b_c$ – is the bias vector for each class. The bias is added to the results of the linear combination $W_c \cdot F_{out}$ for each class, allowing the model to better adapt to the data and improve classification accuracy. This parameter is also learned during model training.

Equation (6) describes the classification process in a neural network, where a fully connected feature-based layer ($\mathrm{F_{out}}$) generates probabilities of belonging to different classes. This is a key step in identification tasks, in particular for face recognition, when the model determines to which class (person) a face image belongs.

The final step involves comparing a set of features or key points of the current image with stored templates. This can be done by calculating the Euclidean distance between the feature vectors:

$$d = \sqrt{\sum_{i=1}^{n}(P_i - T_i)^2}, \qquad (7)$$

$d$ – is a Euclidean distance, which is a measure of similarity between two vectors. The smaller the value of $d$, the closer or more similar the feature vectors are, which corresponds to a higher probability that both vectors represent the same person or object. This is the result of a calculation used for classification or comparison;

$\mathrm{P_i}$ – components of the first feature vector (for example, for the current sample), which was obtained from the neural network after processing the face image. Each component of the vector corresponds to a certain characteristic or feature of the object (person);

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$T_i$ – components of the second feature vector (reference or target vector) with which the first vector $P_i$ is compared. This can be the feature vector for the reference face or the template with which the comparison is made;

$n$ – number of features or dimensionality of vectors. This number determines the number of components used to compare two objects. A feature vector is usually high-dimensional, and the higher the number of features, the more accurate the comparison can be;

$(P_i - T_i)$ – the difference between the corresponding components of two feature vectors. This is the difference between the specific features of the two objects being compared;

$(P_i - T_i)^2$ – the square of the difference between corresponding vector components. The square is used to make all deviations positive and to increase the effect of larger differences on the total distance.

Equation (7) is used to calculate the distance between the feature vectors of two objects. In the context of face recognition, the Euclidean distance $d$ allows us to determine how similar or different the faces are. A small distance means that the faces are similar, and a large distance means that they are different.

## EXPERIMENTAL STUDIES AND ANALYSIS OF THE RESULTS OBTAINED

The purpose of the experiment is to test the accuracy and speed of facial recognition using the developed software code under different lighting conditions at a production checkpoint. The main objectives of the experiment are:

– to assess the impact of the illumination level on the accuracy of facial recognition;

– to determine the time required for real-time facial recognition under different lighting conditions;

– to identify how different viewing angles and the employee's head position affect the system's performance;

– to test the system's resistance to changes in lighting and video stream quality;

– to assess the system's performance in the presence of foreign objects or partial obstacles (e.g., a mask, goggles);

– to determine the optimal conditions for the system's effective operation in real production conditions.

The experiments will be conducted on a Microsoft Surface Pro 4 laptop with the following parameters: Intel 6th generation Core i7 CPU; RAM – 16GB; SSD – 512GB; Intel Iris GPU; The front camera has a resolution of 5 megapixels and supports video recording in 1080p format.

Experimental conditions.

Illumination, different levels of illumination will be used: low (up to 100 lux) – dark room or insufficient lighting; medium (from 100 to 500 lux) – standard daylight; high (over 500 lux) – bright artificial or natural lighting.

Viewing angles, tests will be conducted at different head positions: direct gaze into the camera; slight deviation of the head to the side (15-30 degrees); gaze at an angle (45-60 degrees).

Obstacles, recognition accuracy will be tested in the presence of obstacles, such as: partial coverage of the face (mask, goggles); the presence of objects in the background.

When testing a facial recognition system, it is important to take into account the influence of various factors that can affect its effectiveness. One of these factors is the illumination of the room. To evaluate the system, it is necessary to conduct a series of tests in different lighting conditions, determine the recognition accuracy and frame processing time, as well as identify the minimum level of illumination at which the system is able to function correctly. It is also necessary to conduct tests on changing the position of the employee's head to determine how changing viewing angles affect the accuracy of the system. Particular attention should be paid to situations when part of the face is covered, for example, by a mask or glasses, and assess how much these obstacles reduce the recognition efficiency. In addition, it is important to test the system for its ability to process several

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faces simultaneously, which will allow determining its performance under increased load. The last aspect that should be checked is its resistance to sudden changes in lighting, for example, when an employee moves from a dark room to a brightly lit space, and the speed of the system's adaptation to such changes. The data obtained from the experiment to assess the impact of the level of illumination on the accuracy of face recognition are presented in Table 1.

**Table 1:** Experiment to evaluate the impact of illumination level on face recognition accuracy

| № | Illumination (lux) | Facial recognition accuracy (%) |
|---|---|---|
| 1 | 2 | 3 |
| 1 | 56 | 70 |
| 2 | 76 | 75 |
| 3 | 100 | 81 |
| 4 | 140 | 88 |
| 5 | 250 | 92 |
| 6 | 300 | 94 |
| 1 | 2 | 3 |
| 7 | 400 | 97 |
| 8 | 500 | 93 |
| 9 | 650 | 91 |
| 10 | 700 | 89 |

The first experiment results are presented as a graph in Figure 1.

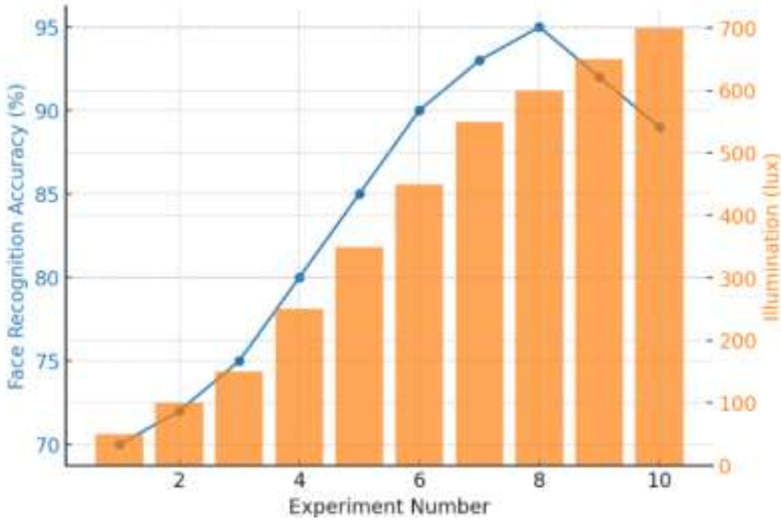


**Figure 1:** Dependence of face recognition accuracy on illumination

The obtained data (Table 1 and Figure 1) show a positive correlation between illuminance in lux and face recognition accuracy. At the initial stages of the experiment, at an illumination of 56 lux, the recognition accuracy was 70%, which is a rather low figure. With an increase in illuminance to 140 lux, the recognition accuracy improves to 88%. However, after reaching an illumination of 400 lux, the accuracy increases to a maximum of 97%. Interestingly, at an illumination of 500 lux, the accuracy decreases to 93%, and at 650 and 700 lux, a slight decrease is observed to 91% and 89%, respectively. This may indicate that excessive illumination can lead to glare or other optical artifacts that negatively affect the quality of recognition. Overall, the data confirms that optimal illumination is critical for the effective operation of the facial recognition system, and the accuracy indicators demonstrate a clear dependence on the level of illumination in the environment.

The results of the experiment on the speed of real-time facial recognition under different lighting conditions are presented in Table 2.

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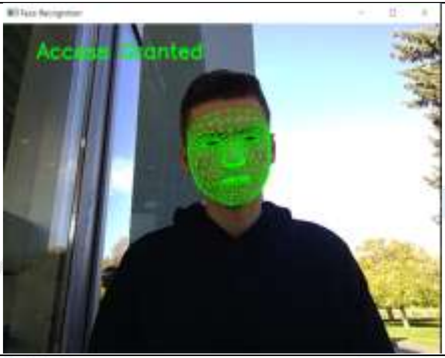
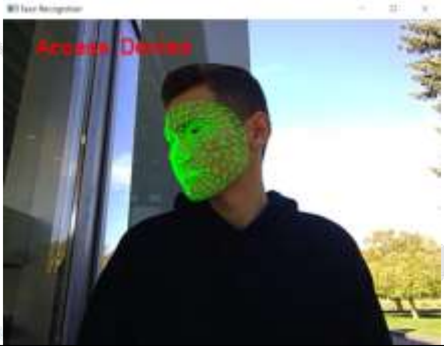
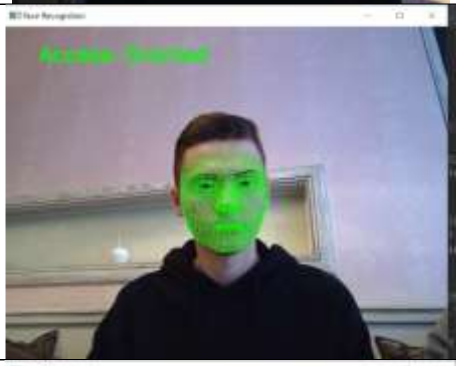
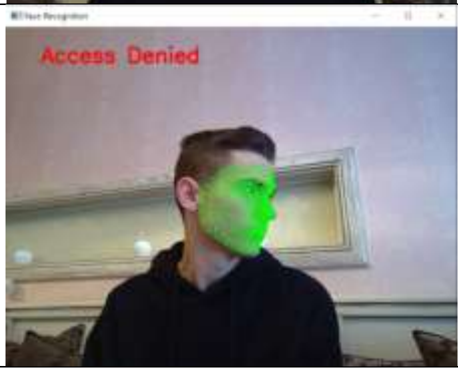
**Table 2:** Real-time face recognition speed under different lighting conditions

| № | Image | Recognition Speed (ms) | Illumination (lux) |
|---|---|---|---|
| 1 | 2 | 3 | 4 |
| 1 |   | 100 | 56 |
| 2 |   | 90 | 76 |
| 3 |   | 78 | 100 |
| 4 |   | 70 | 140 |

The second experiment results are presented as a graph in Figure 2.

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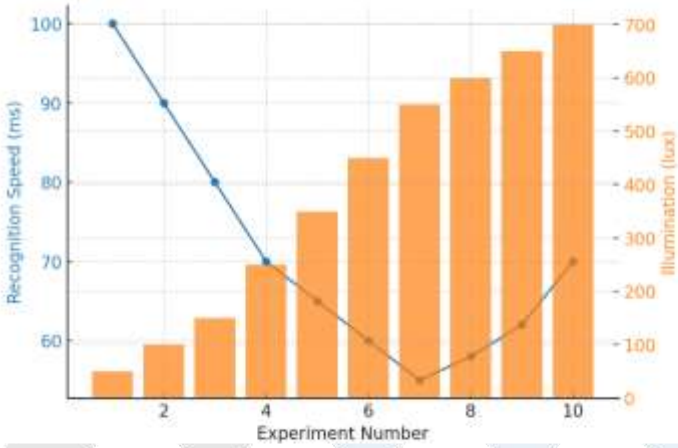


**Figure 2:** Graph of face recognition speed versus illumination

Analysis of the data (Table 2 and Figure 2) obtained from the second experiment shows a clear relationship between the speed of face recognition and the level of illumination. Starting from an illumination of 56 lux, the recognition speed is 100 ms, which is the highest indicator. As the illumination increases to 140 lux, the recognition speed decreases to 70 ms, indicating that increasing the illumination can complicate image processing. With a further increase in illumination to 250 lux, the recognition speed drops to 63 ms, and at 400 lux - to 55 ms, reaching its minimum. It is worth noting that at an illumination of 500 lux, the recognition speed recovers to 60 ms, which may indicate the adaptive capabilities of the system in high illumination conditions. However, at illuminations of 650 and 700 lux, the speed remains constant at 60 and 68 ms, respectively. Overall, these data suggest that optimal illumination is critical for effective facial recognition performance. The findings from the data can be useful for improving image processing algorithms by adapting them to changing lighting conditions.

The experiment results that determine how different viewing angles and employee head positions affect the performance of the system are presented in Table 3.

**Table 3:** Experiment to determine how different viewing angles and employee head positions affect the performance of the system

| № | Viewing angle (degrees) | Recognition accuracy (%) | Recognition speed (ms) |
|---|---|---|---|
| 1 | 0 | 96 | 55 |
| 2 | 15 | 90 | 61 |
| 3 | 20 | 85 | 66 |
| 4 | 30 | 74 | 69 |
| 5 | 45 | 0 | - |
| 6 | 50 | 0 | - |
| 7 | 60 | 0 | - |

The third experiment results are presented as a graph in Figure 3.

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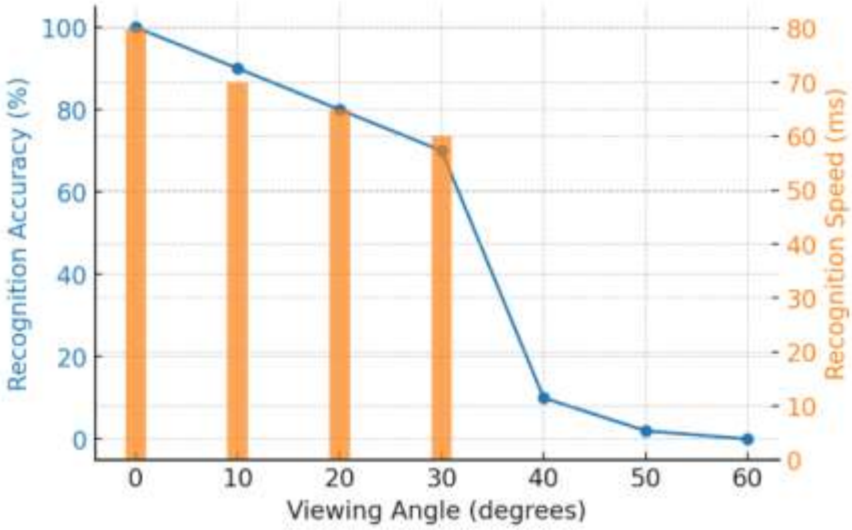


**Figure 3:** The viewing angle effect on the accuracy and speed of face recognition graph

In the experiments investigating the effect of viewing angle on the accuracy and speed of face recognition (Table 3 and Figure 3), seven experiments were conducted. The first four experiments, at viewing angles from 0 to 30 degrees, showed high recognition accuracy, which ranged from 96% to 74%. This indicates that the system effectively recognizes faces with direct and slight side gaze. However, with a head deviation of more than 30 degrees, the accuracy drops sharply to 0%.

The recognition speed shows a positive trend: a decrease in latency from 55 ms with direct gaze to 69 ms at 30 degrees. However, at viewing angles of 45 degrees and more, the system was unable to perform recognition, resulting in the absence of speed data. This indicates that the system needs to be optimized to work with large deviations. Thus, the results suggest that the system is most effective at small viewing angles, and to improve its performance, it is necessary to consider factors that affect face recognition in non-standard conditions.

## CONCLUSION

The study found that the use of the MobileNetV2 neural network in authentication systems allows for a high level of face recognition accuracy while maintaining speed and computational efficiency. Due to its compact architecture and optimized structure, MobileNetV2 demonstrates good performance even on devices with limited computing resources, which makes it suitable for mobile and embedded systems. Experimental results showed that the proposed method is resistant to changes in lighting and facial angles, which significantly increases its reliability in real operating conditions. At the same time, it was found that the recognition quality may decrease when using low-quality images or in the presence of significant changes in the user's appearance. To minimize these effects, it is advisable to use additional image preprocessing mechanisms and adapt the model to specific operating conditions. The analysis showed that MobileNetV2 provides a better balance between speed and accuracy compared to more resource-intensive models such as ResNet or VGG. The results of the study confirm that the implementation of MobileNetV2 in authentication systems can increase their efficiency, reduce delays in processing requests and ensure a high level of security.

An important direction for further research is to improve algorithms to increase resistance to attacks, in particular to fake images and video spoofing. In addition, the use of discoloration technologies and generative models to improve the quality of recognition in low light conditions is promising. Current trends in the field of biometric authentication indicate the need for further integration of artificial intelligence to ensure greater accuracy and security. The study showed that the implementation of MobileNetV2 can significantly reduce the load on computing systems with high recognition efficiency. The practical application of this technology covers a wide range of tasks,

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including access control, identification in mobile devices and face recognition in video surveillance. The results of the work can be used to further optimize biometric identification systems in order to increase their accuracy, speed and protection against unauthorized access. In the future, the development of this technology may lead to the creation of new solutions that combine biometric methods with other security technologies, such as multi-factor authentication and cryptographic data protection methods.

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