Proceedings of the International Conference on Sustainable Computing and Data Communication Systems (ICSCDS-2023)
IEEE Xplore Part Number: CFP23AZ5-ART; ISBN: 978-1-6654-9199-0

2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS) | 978-1-6654-9199-0/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICSCDS56580.2023.10104783

Biometric Verification using Periocular Features based on Convolutional Neural Network

Ms.Srivika S
Department of Information Technology
M.Kumarasamy College ofEngineering
Karur, India
srivikasasikumar@gmail.com

Ms.Gayathri L
Department of Information Technology
M.Kumarasamy College ofEngineering
Karur, India
gayathri2512002@gmail.com

Ms.Nivetha B
Department of Information Technology
M.Kumarasamy College of Engineering
Karur, India
nivethaboopathy78@gmail.com

Ms.Sri Devi N
Department of Information Technology
M.Kumarasamy College of Engineering Karur,
India
sridevi2102001@gmail.com

Mrs.Sujatha R
Department of Information Technology
M.Kumarasamy College of Engineering Karur,
India
sujathar.it@mkce.ac.in

Abstract-Periocular recognition is a biometric identification technology that uses the unique patterns and features of the skin surrounding the eye, such as the eyelids, eyelashes, and eyebrows, to recognize individuals. It is considered a subset of facial recognition technology, as the periocular region is a critical component of the face and contains important distinguishing features. Periocular recognition is becoming increasingly popular due to its high accuracy and usability in a variety of applications, including security and law enforcement, healthcare, and financial services. The process of periocular recognition involves capturing a digital image or video of the periocular region, extracting unique features using computer algorithms, and comparing these features to a pre-existing database of known individuals to identify a match. The network is trained on a collection of periocular pictures and their related IDs in order to employ Xception CNN for periocular identification. The network gains the ability to extract identifying characteristics from these photos that are discriminative. Experimental shows that the Xception CNN provide promising results in the recognition of periocular images.

Index terms: Biometrics, periocular imaging, Convolutional neural network, IRIS datasets, and deep learning.

I. INTRODUCTION

Biometrics [11] is the study of identifying an individual by analysing his or her physiological, behavioural, or chemical characteristics. Voice recognition, facial recognition, and fingerprint scanning are the three most common biometric methods. The biometric system performs a number of tasks in order to establish one's identity. Biometric systems have been shown to have four main parts [12].

A scanner is an actual device that may collect information for a biometric system. The device's capabilities can shift depending on the task at hand; for instance, fingerprint images can be generated by optical sensors, while a face sample could be obtained by means of a camera. [13].

Features extraction algorithm: By applying the extraction approach, important features from the input data are extracted.

Data storage - Fingerprint databases, for instance, collect information about many people's fingerprints and store them alongside other fingerprint databases. The information is stored in an unconventional format for reasons of confidentiality [14].

Depending on the use case, biometric technologies may either verify a user's identity or authenticate their presence in the system. By matching the user's input data to each photograph in the database, the identification system arrives at a conclusion about the person's identity. The authentication mechanism only uses an image if it matches a specified unique identity in the database. There are too many elements that may be removed from a person's biometric data, therefore a trait must meet certain criteria in order to be considered useful[17].

For the purpose of identifying a certain person, a biometric system may utilise a combination of mathematical algorithms and collected biometric data. Biometric systems have several potential uses. In order to utilise some systems, users must first be enrolled in advance. Unlike with other forms of verification, this step is optional in [16].

Enrollment mode is a learning phase that collects biometric data about people for later use in identification. Multiple data collection efforts might be conducted to make the recognition system more or less immune to changes in the data over time. At this point, a biometric sensor is used to capture an individual's unique identifying characteristics, which are subsequently digitally rendered (as signatures) and stored in a central repository. This is because "off-line" processing of enrollment-related information means that it may be completed whenever it is convenient for the user. [18]

In the "one-to-one" comparison verification or authentication mode, the system compares the biometric data submitted with the person's biometric template contained in the system's database to verify the person's identification. In this way, the system must answer the identification question posed by the user [20]. In the present, authentication takes place by smart card, user name, or PIN.

In the "one-to-N" comparison identification mode, the system identifies a person by comparing it to one of the models in the database. It's possible that the person doesn't even exist [20] in the system. The key to this approach is linking a person's id to them directly. Fig(1) shown in below:

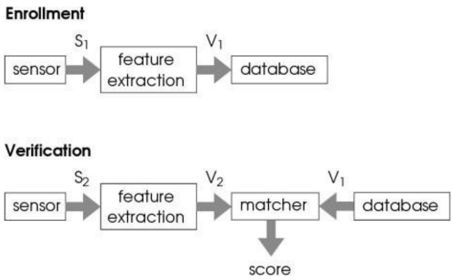


Fig1:Enrollment Verification

II. RELATED WORKS

A number of people, including Fadi Boutros In [1], a new paradigm for biometric identification using HMDs that combines scores from many sources was developed. We performed extensive testing on a real-world database collected from HMD front-facing cameras. Extensive testing showed that our method of fusing iris and periocular score levels significantly outperformed traditional single-modal approaches to verification. The 0.094 EER achieved by the MobileNetV3 model for periocular verification was the best of any single modality, and the 0.0698 EER achieved when this model's findings were merged with those from the iris MobileNetV3 model. For less-than-ideal eye pictures obtained through the Head-Mounted Display device, we found that the periocular modality for biometric verification performed better than the iris modality. We conclude that periocular and iris recognition work well together, and that our proposed multimodal score-level fusion on the periocular and iris modalities significantly increased biometric verification performance. Score-level fusion clearly enhanced the system's overall performance by making it easier to distinguish actual scores from fraudulent ones. The much reduced overlap area after fusion is more evidence of this, confirming the prior results.

With two separate models for left and right, Vedant Kayande et al. [2] were able to predict the participant id. This is because these models were only put through their paces on limited data sets, such as photographs taken from the front with the subject's gaze fixed squarely on the camera. It's safe to assume that if we tested with completely unconstrained data, we'd see a drop in accuracy. We may safely infer that the accuracy would decrease if we tested with entirely uncontrolled data. As it happens, the model has a considerable difficulty separating people with and without glasses. More study is required to implement cross dataset validation, which is presently not possible due to the lack of datasets tailored to the periocular area. When just frontal images were allowed, the data size was drastically decreased, therefore that improvement was also made. Color, hue, and saturation values were adjusted, and a subtle slant was given to the data for quality control purposes. A dual-stream convolutional neural network (CNN) that can recognise periocular objects in the wild utilising both an Orbital Center-Located Binary Coded Patterns and an RGB ocular picture was also proposed by some of Leslie Ching Ow Tiong's co-workers [3]. As a result of fusing the features extracted from the RGB picture and the OCLBCP into two distinct late-fusion layers, recognition performance is strengthened and enhanced. We have collected and disseminated a completely new database, Ethnic-ocular, which is made up of many images of the periocular region taken in the field by people of different ethnic backgrounds. Extensive testing on the newly released Ethnic-ocular database and publicly available datasets showed that the proposed network beat several competing networks in recognition and verification tasks. The suggested network makes use of the colour information included in the RGB picture, and you've shown how the OCLBCP descriptor may boost recognition performance. We publish and make accessible for benchmarking an Ethnic-ocular database of periocular from the wild. The proposed network has also been analysed using CASIA-iris distance, UBIPr, and AR, three freely accessible datasets. It was shown that the proposed network beat many competing networks in both identification and verification tasks on these datasets.

Luiz A. Zanlorensi et al. [4] developed a fresh periocular dataset that includes images shot in unconstrained conditions throughout several sessions using a wide range of mobile device types. The primary objective was to collect images from the actual environment and annotate them with data about the periocular area's lighting and noise levels. More than a thousand subjects were sampled, making this the biggest periocular dataset in the literature. It also features the most sensor types (196). For this reason, we conducted an ablation study on this model to identify the tasks that contributed most to the results. After determining the kind of mobile device, the ages of its users, sex, and dominant eye are ranked as the next most important steps. Notably, we didn't conduct any experiments with just one eye or sex-segregated pictures. The model trained with all these tasks best reported identification and verification outcomes in closed and open-world protocols.

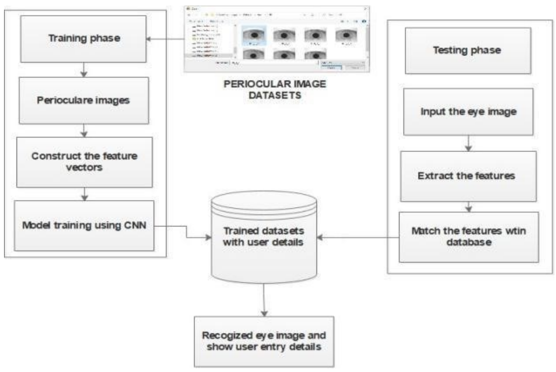
Considering the small size of most biometric datasets, Kevin Hernandez-Diaz and colleagues [5] investigated a new method of cross-sensor periocular biometrics that does not rely on the usage of deep neural networks to extract features. Across addition to improving identification in a wide range of wavelengths, it also produces very good cross-spectral matching results. In this study, we use the IIITD Multispectral Periocular Database to conduct experiments verifying periocular identification across three spectral regions: the visible, night vision, and near infrared. We use the well-known CNN architecture Res -Net that has been pre-trained using the ImageNet database, and we compare the features retrieved at each layer using unsupervised similarity metrics such as the 2 distance and the cosine similitude between vectors. In addition, we train a neural network to enhance the outcomes of the first approach.

In order to identify patterns with little pre-processing, Punam Kumari et al. [6] implemented the work on the pixels of the pictures. The potential for growth in knowledge of such models is substantial. Convolutional neural networks may be trained either from scratch or using the Transfer Learning method to be used for recognition. This article uses seven different commercially available deep CNN models to evaluate the periocular area in two imperfect settings. The first problem was solved by 19 with a recognition accuracy of 94% for photos with a 30 degree pose variation and 96% for images with a -30 degree pose variation, while the second problem was solved by RES NET 18 with a recognition accuracy of 88% for matching images on the same side. A unique technique using mirror images of testing dataset is also offered to increase the recognition accuracy for matching between pictures captured from opposite sides of the periocular region, and the results show a significant uptick in recognition precision.

There was a proposal for deep learning-based periocular identification made by Amani Alahmadi et al. [7], which used a pre-trained CNN model for discriminative feature extraction and a Sparsity Augmented Collaborative Representation-based Classifier to identify eyes (SA-CRC). Because of the abundance of data and sparsity encoded in the activations of the convolutional layers, principle component analysis has been presented as a powerful and effective tool for feature extraction. We compared the system's performance when using convolutional layers versus fully connected layers to extract features, and we found that the features extracted from convolutional layers are more discriminative and robust than those obtained from FC layers, with the final level of convolutional layers yielding the most discriminative representation. Extensive trials confirmed that the characteristics learned during the training phase of a convolutional neural network (CNN) performed effectively on a periocular recognition task (verification and identification). To ascertain the impact of domain on a pertaining CNN model, we tested the performance of the system with two distinct CNN models, VGG-Face (pertained on face data) and VGG-Net (pertained on ImageNet data). The results demonstrate that the system performs just as well when a CNN model that has been previously trained on any relevant domain is used; as a result, Conv SRC is domain-independent. One key factor in the success of the suggested strategy is the SA-CRC classifier. The SA-CRC approach was evaluated against the state-of-the-art KNN method, and the findings showed that the former is superior in terms of recognition performance.

Vineetha From a deep learning standpoint, multispectral periocular recognition has been handled by Mary Ipe et al. [10]. Our results demonstrate that using pre-built CNN features may significantly boost recognition accuracy. Although convolutional neural networks (CNNs) like Alexnet are excellent in storing discriminative characteristics for periocular identification, there are many unanswered problems and obstacles surrounding the use of deep learning to this topic. By employing model reduction strategies like pruning and compression, CNNs used for recognition tasks can handle the computational complexity of the task at hand. Super-resolution, a method for enhancing picture resolution, may help improve the near infrared images' poor accuracy. In addition, the same deep learning strategy may be used to the problem of cross-spectral periocular identification. Recent progress in Deep Reinforcement Learning and Evolution Theory has made it possible for the networks to optimise themselves for the periocular recognition problem.

III. PROPOSED METHODOLOGY



The Xception CNN architecture is a deep neural network that consists of multiple layers of convolutional, pooling, and activation functions. Here are the formulas for some of the key layers in the Xception architecture:

Depthwise convolution: Applies a convolution operation to each channel of the input feature map separately. Let X be the input feature map with dimensions H x W x C, where H is the height, W is the width, and C is the number of channels. Let K be the depth wise convolution kernel with dimensions F x F x C, where F is the kernel size. The output feature map is obtained by applying K to each channel of X separately. The output feature map has dimensions H x W x

Pointwise convolution: Applies a 1x1 convolution operation to the output feature map of the depth wise convolution. This operation is used to combine information from different channels. Let Y be the output feature map of the depth wise convolution with dimensions H x W x C. Let L be the pointwise convolution kernel with dimensions 1 x 1 x C x D, where D is the number of output channels. The output feature map is obtained by applying L to Y. The output feature map has dimensions H x W x D. The formula for depth wise separable convolution is: Y = L * (K * X)

Batch normalization: Batch normalization is a technique used to normalize the activations of the previous layer to improve the training stability and speed of the network. Let X be the input feature map with dimensions H x W x C. Let mu and sigma be the mean and standard deviation of the activations over the batch axis. The normalized feature map is obtained by applying the following formula: Y = (X - mu) / sqrt(sigma^2 + epsilon) where epsilon is a small constant added for numerical stability.

Global average pooling: Global average pooling is a pooling operation that computes the average of the activations over the entire feature map. Let X be the input feature map with dimensions H x W x C. The output feature map is obtained by applying the following formula: Y = 1/(H*W) * sum(sum(X)) where Y is a vector with dimensions C 1. These are some of the key formulas used in the Xception CNN architecture. However, the full architecture is more complex and involves additional layers, such as convolutional and fully connected layers, that are used for classification and feature extraction

Data collection: Description Amass a sizable collection of periocular pictures and the IDs that go with them. To ensure the model's durability, the photos should be of the highest quality and taken in a variety of lighting situations and positions.

Data pre-processing: Pre-process the periocular images by cropping the images to include only the periocular region and resizing them to a fixed size. This ensures that the input images are consistent in size and focus on the relevant region.

Splitting the data: Create training, validation, and testing sets from the data. The validation set is used to fine-tune the model's hyperparameters, the testing set is used to assess the

Fig 2: System Architecture

model's performance, and the training set is used to train the model.

Training: Train the network on the training set using backpropagation to adjust the weights. Monitor the model's performance on the validation set and adjust the hyperparameters as needed to improve performance. Evaluation: Evaluate the model's performance on the testing set using metrics such as accuracy and AUC.

Matching: Compare the extracted features to the pre-existing database of known individuals using a similarity measure. The individual with the closest matching features is considered the identified individual.Overall, using Xception CNN for periocular recognition involves collecting and preprocessing the data, fine-tuning a pre-trained model using transfer learning, training the model on the dataset, evaluating the model's performance, and using the trained model to extract features from new images and identify individuals.

IV. FEATURE EXTRACTION

The process of finding and measuring the distinct texture and form traits of the skin and iris areas around the eye is known as feature extraction in periocular image analysis. For periocular identification, a variety of feature extraction methods may be employed, including both manually created feature descriptors and learnt features using deep learning models. The process of finding and measuring the distinct texture and form traits of the skin and iris areas around the eye is known as feature extraction in periocular image analysis. For periocular identification, a variety of feature extraction methods may be employed, including both manually created feature descriptors and learnt features using deep learning models. In general, the aim of feature extraction in periocular image analysis is to extract discriminative features resilient to fluctuations in illumination, position, and expression, which may properly reflect the distinctive properties of the skin and iris areas around the eye.

V. SELECTION OF CNN

High accuracy: In periocular image recognition, CNN-based techniques have been found to achieve excellent accuracy, frequently beating more conventional techniques. This is because CNNs are better able to capture the distinctive properties of the periocular area since they can automatically train to extract discriminative aspects from the image.

VI. AUTHENTICATION METHODS

Authentication, the determination of whether or not a person must be granted access to a system or resource, is a crucial issue in the study of security. Confidentiality and integrity are essential parts of the authentication process. Further, any authentication resource is the first line of defence. Use authentication as a service here to keep your resources safe. It's crucial that equal authentication isn't applied in every possible circumstance. It's inconvenient that consumers often need to use different passwords for their bank, their social media, and their favourite online stores. There will be more noise because people will forget their passwords or get them mixed up due to the wide range of passwords. An authentication scheme's legitimacy is heavily dependent on its resistance to assaults and the degree to which it needs user and server cooperation. This implies that both the client and the server must participate in the authentication processes.

This system's inspiration, however, may be used in other contexts where privacy and data integrity are of paramount importance. With the help of Implicit Password, the proposed Authentication System has been applied to the banking industry. If the scheme allows any picture to be used and doesn't need certain clickable regions to have well defined borders, then the password might be any set of points inside the image with slight variations. In IPAS, the server already knows the relevant information—the user's password—during authentication, and the user provides this information to the server during registration, although in an implicit form. Although it may be used with any computer system, the implicit password is most suited for mobile devices and portable PCs. Simply authentication is the process through which the identity of a user is verified. This is often accomplished using a login name and password. If the user provides their username, the device will use that information to authenticate their identity, on the assumption that most effective the user and the website's server know the user's password. In order for the website authentication method to function, it compares the user's credentials to those already on file. When a match is found, the authentication procedure is finished.

Biometric Authentication: A user's biological characteristics may be used in conjunction with other authentication variables to create a strong biometric authentication. Although this seems futuristic, you've undoubtedly already used it to unlock your smartphone. Although fingerprint scanning remains the most common method of biometric authentication, developers are increasingly turning to facial recognition software. Hackers have a more difficult time duplicating a user's biological factors, but it's important to note that these authentication techniques are typically considerably less safe than you'd originally expect. Smartphone fingerprint scanners, for example, can only record a limited piece of your fingerprint because of their size. An incomplete fingerprint picture is less reliable than a complete one. Keep in mind that even if a user's fingerprints are stolen, the biometric authentication system cannot be modified. While the future of biometric authentication seems bright, for the time being it serves best as a secondary login option to strengthen an existing system.

Limitations in traditional authentication systems: Deformed and noisy data from sensors due to defects or lack of maintenance (such as dirt building up on a fingerprint sensor). As a result of high levels of overlap across feature classes, defining traits of people may be gleaned. The term "non-universality" refers to a biometric's inability to obtain useful biometric data from a set of users because of inconsistencies and errors in the acquired biometric data. A significant percentage of the population (approximately 4 percent) may have scars or cuts in their fingerprints. Therefore, a fingerprint biometric system may incorrectly extract fine details from them. The sensor-user interface has been improperly calibrated.

Spoof attacks, in which a false user's attributes or biometrics are registered in the template database and then exploited to fool the system into thinking the real user is there. That is, the authentication mechanism may be fooled using a fake finger or fingerprint. This is a typical kind of assault that makes use of observable behavioural traits.

VII. PERIOCULAR BASED AUTHENTICATION SYSTEM

Researchers have recently been interested in ocular biometrics in free-ranging settings, particularly with photos recorded by mobile devices and at visible wavelength. When the iris characteristic cannot be acquired because of occlusions or inadequate picture quality, periocular recognition has been shown to be a viable substitute. It's true that the iris characteristic is very distinctive, but the periocular trait doesn't come close. It is thus essential to employ large datasets consisting of many people to evaluate biometric systems' ability to extract discriminatory information from the periocular area. Finally, it is crucial to employ datasets comprising photos of the same subject collected in several sessions to address the within-class variability induced by illumination and features in the periocular area. In the field of biometrics known as 'periocular-based', features from the area of the face around the eye are used to automatically identify or classify a person..

Just lately, the most well-known techniques for image identification were revealed, and they all make use of deep learning. Human verification by biometric samples is the standard procedure. The main obstacle in disciplines like computer vision is the very high cost of developing, training, and deploying such models for the purpose of expanding existing applications. Transfer learning offers versatile approaches to effectively model the proper Convolutional Neural network (CNN) to address this problem. A convolutional neural network (CNN) trained on a big dataset including a large number of classes is fitted in such a manner to the current taxonomizing challenge. Because of its nature and the fact that each individual provides two samples—one from each eye, or iris—the periocular region is one of the most difficult biometric regions to analyse. This paper presents a transfer learning framework that utilises three popular CNN models to simulate a periocular-based person recognition model. Xception CNN, one of the most well-known CNN models, is used to conduct in-depth research and analysis on the chosen CASIA iris picture database.

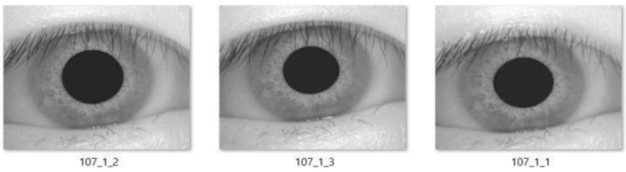


Fig 3: CASIA eye database

CASIA, a Chinese research institute, stands for "Chinese Academy of Sciences Institute of Automation." The institution built the CASIA Iris Database, a collection of iris photographs used in iris recognition research. More than a thousand participants' iris photographs from both visible and near-infrared light sources are included in the collection, with each subject submitting two iris photos (one for each eye). One of the biggest publicly accessible collections of iris photos is the CASIA Iris Database, which is often used in studies on iris recognition, biometrics, and computer vision.As may be seen in the above picture, a publicly available database known as CASIA provides eye images for use in building IRIS-based biometric attendance models. In this way, it is possible to quickly and accurately identify a person by their unique IRIS patterns in each eye. Five pictures representing 10 different people are included in the 460 total images in this collection. Using an existing database, IRIS segmentation may be used to either uniquely identify a person or categorise an IRIS picture.

Pre-trained CNN Models

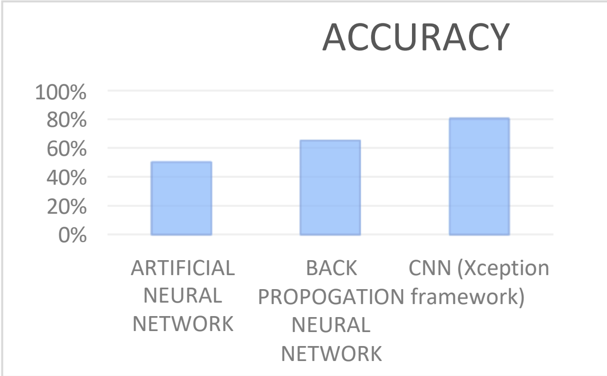
After being trained on the ImageNet dataset, the Convolutional Neural Network (CNN) known as Xception has been shown to achieve an accuracy rate of over 70%, making it a popular choice for use in image recognition applications. Multiple ideas discovered by scientists throughout time have coalesced into one single paradigm. To create the Inception-v3, the developers used a deep neural network with 42 layers. Convolutions, max-pooling layers, average pooling, dropouts, and FC layers make up the inception-v3 model. Regularizers of various kinds (L1, L2) are used to enhance the learning process, while weight regularizers are used to encourage the network to support small weights. It's a generic method for making models more generalizable by reducing the amount of time spent on training. The training of networks is drastically altered by the inclusion of the batch normalisation layer. It makes the landscape of the associated optimization problem much less bumpy.
Gradients become more stable in this manner, opening the door to using a broader range of learning rates and speeding up network convergence. Using a dropout layer as a generalisation technique, most large network architectures can be generalised.

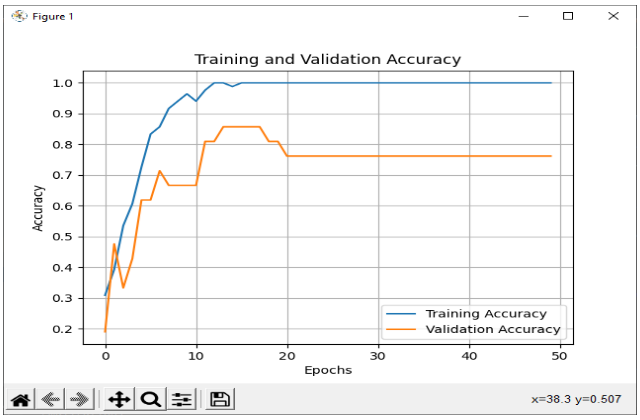
VIII. RESULTS AND DISCUSSION

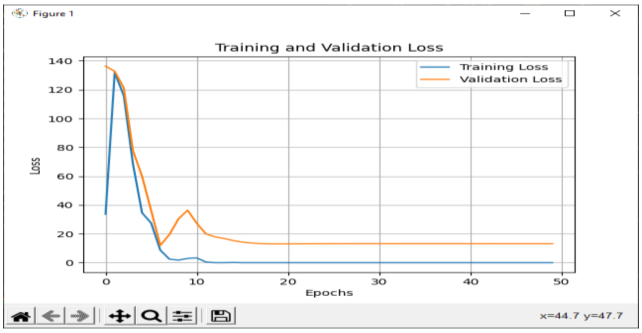
Various methods of measuring performance have been used in studies of image classification. This study also employs these metrics to evaluate the precision and consistency of the classification procedure. The accuracy of the model is just one of many factors that go into determining how useful it is. Calculating the percentage of correct predictions relative to the total number of test data yields the accuracy (ACC). It is also expressed as 1 minus the error rate (ERR). There is no better accuracy than 1.0, and the worst possible is 0.0.

$$ACC = \frac{TP+TN}{TP+TN+FN+FP} \times 100$$

ALGORITHM	ACCURACY
ARTIFICIAL NEURAL NETWORK	50%
BACK PROPOGATION NEURAL NETWORK	65%
CNN (Xception framework)	80%







The accuracy rate of periocular image recognition systems depends on various factors, including the quality and quantity of the training data, the pre-processing and feature extraction techniques used, the classifier employed, and the evaluation metrics used. However, in general, CNN-based periocular image recognition systems have been shown to achieve high accuracy rates. Furthermore, CNN-based periocular recognition systems have been shown to be robust to various challenges, such as variations in lighting, pose, expression, and occlusion. For example, a study on periocular recognition in the wild, which included images captured in uncontrolled environments, achieved a recognition rate of 80% using a CNN-based approach. Overall, the accuracy rate of periocular image recognition systems is dependent on various factors and can vary depending on the dataset and evaluation metrics used. However, CNN-based periocular recognition systems have shown to achieve high accuracy rates and can be effective for various applications in biometrics, surveillance, and security.

IX. CONCLUSION

In this study, we provide a novel periocular dataset consisting of photos taken by a variety of mobile device models in uncontrolled settings over separate sessions. The primary goal was to compile a database of photos taken in natural settings, including information on the periocular area, such as the amount of light, the presence of background noise, and other characteristics of the images. In this research, we built a convolutional neural network (CNN) model using periocular pictures to provide an effectively for detecting these anomalies. Most significantly, regularisation block layers were included as a bridge between the CNNs in the network. All networks in the research were equipped with pre-trained parameters to facilitate knowledge transmission. These models were first built using the ImageNet database as their basis for pre-training. When compared to other models, the Xception CNN model has the highest accuracy. A trustworthy periocular condition system may be provided via an architecture based on regularisation. Adjusting the parameters of these models could make them more precise.

REFERENCES

[1] Boutros, Fadi, et al. "Fusing iris and periocular region for user verification in head mounted displays." 2020 IEEE 23rd International Conference on Information Fusion (FUSION). IEEE, 2020.

[2] Kayande, Vedant, et al. "Periocular Recognition using CNN based Feature Extraction and classification." 2021 10th IEEE International Conference on Communication Systems and Network

Technologies (CSNT). IEEE, 2021.

[3] Tiong, Leslie Ching Ow, Yunli Lee, and Andrew BengJin Teoh. "Periocular recognition in the wild: Implementation of RGB-OCLBCP dual-stream CNN." Applied Sciences 9.13 (2019): 2709.

[4] Zanlorensi, Luiz A., et al. "A new periocular dataset collected by mobile devices in unconstrained scenarios." Scientific Reports 12.1 (2022): 17989.

[5] Hernandez-Diaz, Kevin, Fernando Alonso-Fernandez, and Josef Bigun. "Cross spectral periocular matching using resnet features." 2019 International Conference on Biometrics (ICB). IEEE, 2019.

[6] Kumari, Punam, and K. R. Seeja. "Periocular Biometrics for non-ideal images: With off-the-shelf Deep CNN & Transfer Learning approach." Procedia Computer Science 167 (2020): 344-352.

[7] Alahmadi, Amani, et al. "ConvSRC: SmartPhone-based periocular recognition using deep convolutional neural network and sparsity augmented collaborative representation." Journal of Intelligent & Fuzzy Systems 38.3 (2020): 3041-3057.

[8] Dhar, Prithviraj, et al. "EyePAD++: A Distillation-based approach for joint Eye Authentication and Presentation Attack Detection using Periocular Images." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2022.

[9] Badejo, Joke A., Adekunle A. Akinrinmade, and Emmanuel Adetiba. "Survey of Periocular Recognition Techniques." Journal of Engineering Science & Technology Review 12.5 (2019).

[10] Ipe, Vineetha Mary, and Tony Thomas. "Cnn based periocular recognition using multispectral images." Advances in Signal Processing and Intelligent Recognition Systems: 5th International Symposium, SIRS 2019, Trivandrum, India, December 18–21, 2019, Revised Selected Papers 5. Springer Singapore, 2020

[11] V. N. Boddeti, J. M. Smereka, and B. V. K. V. Kumar, ''A comparative evaluation of iris and ocular recognition methods on challenging ocular images,'' in Proc. Int. Joint Conf. Biometrics (IJCB), Oct. 2011, pp. 1–8,

[12] C. E. Rogers, A. W. Witt, A. D. Solomon, and K. K. Venkatasubramanian, ''An approach for user identification for head-mounted displays,'' in Proc. ACM Int. Symp. Wearable Comput. ISWC, 2015, pp. 143–146

[13] C. George, M. Khamis, E. von Zezschwitz, H. Schmidt, M. Burger, F. Alt, and H. Hussmann, ''Seamless and secure VR: Adapting and evaluating established authentication systems for virtual reality,'' in Proc. Workshop Usable Secur., 2017, pp. 1–12

[14] M. Alsaadi, ''Physiological biometric authentication systems, advantages, disadvantages and future development: A review,'' Int. J. Sci. Technol. Res., vol. 4, pp. 285–289, Oct. 2015.