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Comparative analysis of Post-mortem Iris Reorganization System using Deep Learning Approach

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1.Introduction

The word "biometric" refers to the identification and verification of an individual's identity based on the individual's distinctive traits or characteristics [1]. Physiological and behavioural aspects are combined in biometric systems. Physiological characteristics are a subset of biometrics that contains physiological and biological qualities that are influenced by a biometric system. It includes DNA, Hand, Face, Earlobe, and Iris, among other things. Behavioral characteristics are a subset of biometrics that are concerned with non-physiological or non-biological traits that are influenced by a biometric system. Signature, voice, gait, and keystroke recognition are the four categories [2].

Personal IDs are becoming increasingly necessary to fulfil the security needs of today's networked world. Token-based approaches or knowledge-based methods are the two most used ways for personal IDs. For authentication, token-based techniques employ keys or ID cards, whereas knowledge-based methods use the user's predefined code or password.

Conventional techniques, on the other hand, become unreliable if the token is lost or the password is forgotten, hence the need for new and developed dependable ways for personal identification is becoming an increasingly significant study subject. Because the iris is stable and does not vary throughout life, it is one of the most reliable means for identifying people. Furthermore, even for twins, it is difficult to discover two people with identical iris traits [3]. As depicted in Figure 1-1, the iris is a circular anatomical structure that lies between the cornea and the lens of the eye. The iris' job is to regulate the amount of light that enters the pupil via the sphincter and dilator muscles, which govern the pupil's size. The pupil size is between 10% and 80% of the iris diameter, and the typical iris diameter is between 11.6 mm and 12.0 mm. The epithelial layer, which includes intense pigmentation cells, and the stroma layer, which contains blood vessels, make up the human iris. It is responsible for shrinking the pupil size. The epithelial layer is on top of this layer.

Iris identification is a technique for identifying persons based on the iris's distinctive characteristics. In addition, the iris is generally grey, blue, brown, or green in hue. Iris recognition is a kind of biometric authentication [4]. Flom and Safir introduced the first iris recognition idea in 1987. They presented a set of highly regulated and non-functional lighting settings to adjust the illumination such that the pupil size in all photos is the same for proper Iris segmentation. They outlined the basic subsystems of an iris recognition system, including image acquisition, preprocessing, Iris segmentation, Iris analysis, feature extraction, classification, and appropriate image processing and pattern recognition techniques, as well as image processing and pattern recognition techniques. This theoretical study on Iris recognition system has been used as a foundation for all actual Iris recognition system techniques. The six key phases of a typical iris recognition system are as follows: [5]. The first step is image acquisition, which involves taking a number of photographs of the iris using cameras in order to guarantee that the best images are captured, allowing for more flexibility and recognition. The second step is picture preparation, which involves controlling the image's size, colour, and brightness in order to prepare it for segmentation.

The third step is segmentation, which involves detecting the iris and pupil boundaries, as well as eyelids and eyelashes. Normalization, the fourth step, entails transforming the iris area into a rectangular shape. Feature extraction, the fifth step, takes characteristics from the normalised iris picture and encodes them into a design that can be recognised. The classification step of an iris recognition system compares the characteristics obtained by photographing the iris with features recorded in the database.

2. Design and Implementation

The below systematic representation shows the Machine Learning Approaches for Post-mortem Iris Detection System.

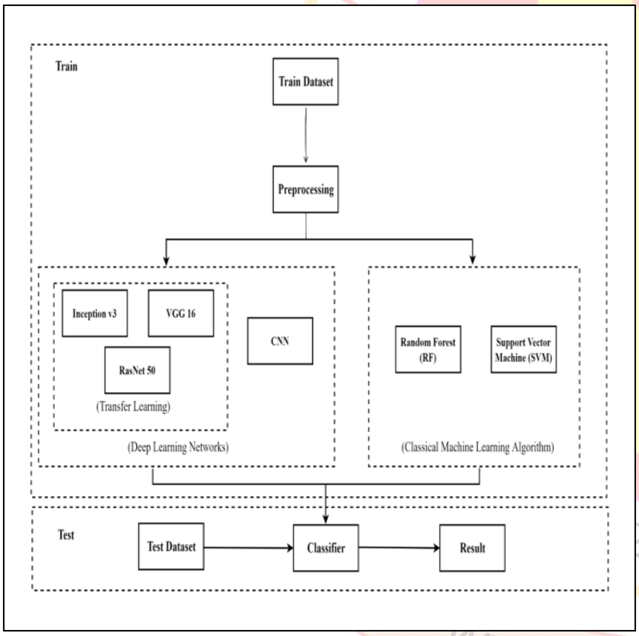

Fig. 1: Workflow of Approaches for Post-mortem Iris Detection System

3. Discussion and Conclusion

3.1 Datasets for Experimentation

The "Warsaw-BioBase-Post-Mortem-Iris v3.0 and v4.0" dataset utilised by the Post-mortem Iris Detection System is a collection of data created by Warsaw University of Technology in Poland in partnership with Medical University of Warsaw in Poland. The Dataset contains photos of post-mortem irises taken under visible and near-infrared light. The overall goal of producing and distributing the Dataset is to aid researchers in their efforts to improve the reliability of iris identification for post-mortem samples. WUT controls the Dataset's copyright and is the exclusive source for this data.

3.2 Process and Method of Evaluation

The CLDC process is described in four primary steps. The first phase is the collection and organisation of the image dataset of post-mortem iris scans into different folders depending on versions and individuals for classification under the guidance of experts. The data is imported and preprocessed in the second step, which includes scaling to a standard size before being separated into test and train data. In the third step, the model is built using training data that has been supplemented to avoid overfitting and to generalise the model for higher prediction accuracy on unknown data. The model's performance is tested using the test data in the last step.

Because the study is based on classification, the accuracy, precision, recall, and f1 score are the performance measures utilised to assess the model's performance. To find the best model, all of the produced models are compared to these measures, which include three CNN models with several layers and a transfer learning technique, as well as two standard machine learning algorithms, SVM and Random Forest. Below is a quick rundown of what each indicator represents in terms of current research.

		Predicted	
		Positive	Negative
Observed	Positive	TP	FN
	Negative	FP	TN

Table 1: Confusion Matrix

True positives (TP) are positive tuples that the classifier successfully classified, while true negatives (TN) are negative tuples that the classifier correctly labelled. False positives (FP) are negative tuples that have been tagged wrongly. False negatives (FN) are positive tuples that have been tagged wrongly. Performance is assessed in terms of accuracy in table 1 and is calculated using the method below. The proportion of accurate predictions is referred to as accuracy.

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

Precision:

The proportion of accurately categorised occurrences or samples among those labelled as positives is measured by precision.

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

Recall:

The recall is the measure of our model correctly identifying True Positives.

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

4 Result

4.1 Classical Machine Learning Algorithms

a. Random Forest (RF) results

For the identification and categorization of post-mortem iris pictures, a Random Forest classification model was used. The dataset that was used to train and test the classification model using stratified 5-fold cross-validations. Three performance measures are used to calculate the outcomes of the experiment. Table 2 shows the performance parameters accuracy, precision, and recall. The Random Forest model predicted a 91.5 percent accuracy.

	Accuracy	Precision	Recall
Split 1	91.1%	91.2%	91%
Split 2	88.4%	88.2%	88.8%
Split 3	92.2%	93.3%	92.6%
Split 4	93.6%	85%	92.7%
Split 5	92.5%	93.8%	90.4%
Average	91.5%	92.3%	91.1%

Table 2: Results of Random Forest

4.2 Support Vector Machine (SVM) results

Stratified K Fold Cross Validation is used to train and test the SVM classification model for the four types of post-mortem iris pictures included in the dataset. The data is fed into the classification model using Stratified k fold cross-validation, which divides the data into training and testing groups.

	Accuracy	Precision	Recall
Split 1	93.3%	93.8%	95.4%
Split 2	95.2%	95.6%	96.5%
Split 3	93.5%	95.2%	92.1%
Split 4	97.3%	98%	96.5%
Split 5	96.2%	96.4%	93.6%
Average	95.1%	95.8%	94.7%

Table 3: Results Support Vector Machine

The validation results (Table 3) indicate better prediction results from SVM, with a prediction accuracy of 95% than from Random Forest 91%.

4.3 Deep Learning Algorithms

a. CNN

First, a simple CNN was developed using Keras, a deep learning framework with built-in layers such as convolution, max pooling, and so on. The accuracy of a customised CNN with various layers was tested. A dropout layer was utilised to prevent overfitting. The hidden layer was activated using relu, and the dense layer was activated with softmax at the end. Other hyperparameters such as batch size, learning rates of 0.01 and 0.1, epochs, and optimizers such as adam and SGD were also fine-tuned. The prediction accuracy of the CNN models was 90%.

b. Transfer learning using Inception v3, VGG16, and ResNet 50

Transfer learning is a method of using a previously learned model to solve a new issue. The transfer learning approach has the benefit of using low computer resources while simultaneously reducing training time. Inception v3, VGG 16, and ResNet 50 are used as transfer learning models. The default size of this architecture is 224 * 224 pixels, therefore models are run on that scale. This is accomplished by adding a few more thick layers to the already-trained network and freezing the other levels. The Inception v3 model has the highest prediction accuracy of 99 percent, followed by the VGG 16 at 98 percent and ResNet 50 at 96 percent.

4.4 Model Comparison

We may deduce from the numbers in Table 4 that the Inception v3 transfer learning architecture is the best for categorising post-mortem iris pictures since it has greater accuracy, precision, and recall scores than other models. It received a 99 percent accuracy rating, with VGG16 coming in second. These findings show that transfer learning approaches based on CNN are superior than conventional models for identifying and classifying post-mortem iris pictures, so satisfying our study goal. The training data included enhanced photos, which increased the model's efficiency, as seen by the accuracy and other metric values.

Algorithm	Accuracy
Inception v3	99%
VGG 16	98%
ResNet 50	96%
Support Vector Machine	95.1%
Random Forest	91.5%
CNN	90%

Table 4: Results

5. Conclusion

The conclusion drawn encourages using the CNN-based transfer learning model Inception v3 for the classification of post-mortem iris images, thus satisfying the objectives of the research. Image augmentation used in the model helps the transfer learning architecture to predict better on the unseen data. Inception v3 performed best among the models used. However, they took a lot of training time.

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