

**VA: VISION ACUTALIZATION A NOVEL CNN MODEL FOR HUMAN IRIS
COLOR DITECTION USING DEEP LEARING.**

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This Report Presented in Partial Fulfillment of the Requirements for the
Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled “**VA: VISION ACUTALIZATION A NOVEL CNN MODEL FOR HUMAN IRIS COLOR DITECTOR USING DEEP LEARING.**”, submitted by **Md. Mahadi Hasan Sany, Jahid Hasan Shamim, and Iktiar Alam Pranto, ID NO: 181-15-11173, 181-15-11186, and 181-15-11198** to the Daffodil International University's Department of Computer Science and Engineering, has been acknowledged as adequate for the partial fulfillment of the criteria for the degree of B.Sc. in Computer Science and Engineering, and has been approved in terms of style and content. The presentation took held on 5th January, 2022.

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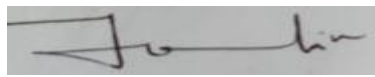


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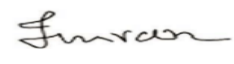


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DECLARATION

We hereby declare that we completed this project under the supervision of **Ms. Sharun Akter Khushbu, Lecturer, and department of the CSE** Daffodil International University Department of CSE. We also certify that no component of this project, or any part of it, has been submitted to any other institution for the award of a degree or diploma.

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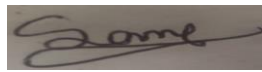
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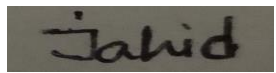


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We would like to express our gratitude to all of our Daffodil International University classmates who participated in this discussion while completing their course work.

Finally, we must recognize and acknowledge our parents' unwavering support and patience.

ABSTRACT

By evaluating the trained dataset, a deep learning model produces astonishing results for image processing. A Deep learning method has been utilized in our research to automatically identify iris color, and this system has a dataset of 2705 photos from five different species of iris. To categorize iris color, four Convolutional Neural Network (CNN) models were used. These models produce more accurate picture classification results. The image data must be preprocessed before these models can be applied. Data preparation necessitates the use of certain methods. RGB conversion, filtering, resize & rescaling, and categorization are the options. Following the application of these methods, image data is preprocessed and prepared for use in classifier algorithms. The suggested model has a 90% accuracy rate and was cross-validated using stratified Cross-Validation. After that, a transfer learning model called "ResNetV2" was used, which resulted in a score of 74.55 % accuracy.

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CHAPTER 1

Introduction

The iris is a pigmented muscular curtain located in the front of the eye, between the cornea and the lens, and is perforated by an opening called the pupil. In front of the lens and the basal body, the iris is located behind the cornea. A fluid known as eye lens surrounds it on all sides. Dilation (expansion) and contraction (contraction) are the opposing functions of the iris, which are made up of two smooth muscle sheets (constriction). These muscles regulate the size of the pupil and, as a result, the amount of light that reaches the sensory tissue of the retina. In bright light, the iris sphincter muscle constricts the pupil, whilst the iris dilator muscle contracts and expands the opening. The amount of pigment in the iris determines eye color. When there isn't much pigment in the eye, it appears blue. As the pigment level grows, the hue shifts from deep brown to black.

In the world, there are eight different colors of iris. Here we took six variants of Iris color: Amber, Blue, Brown, Gray, Green, Heterochromia. We will build up a neural network model to detect the iris color. Iris is a unique biometric feature for every person globally, but the color will be matched from person to person. We are working with color, and color detection can be a significant task to conclude eye diseases such as Diabetic Retinopathy, Glaucoma, Amblyopia, etc.

In this project, we have only worked on color detection rather than disease identification, and in that case, the dataset will be different according to regular iris collection. Where our proposed model can detect the normal natural iris color. On the other hand disease effected eye is totally different form normal. During the detection of iris color our model will learn about the normal eye pattern which will help to differentiate form disease effected eye.

Environment plays a vital role when the image is taken into consideration. Because accuracy depends on the environment that influences the data processing stage, a domain can be constrained or unconstrained based on lighting conditions [1] [2]. The data captured in an uncooperative environment creates impurity that affects accuracy that is the cause of accuracy falling on different practice models.

So after getting the data, our priority will be the proper processing of that data for fitting the model we prefer. In the process of inputting image data, many practical approaches for recognition are proposed by many authors, for example, the Multimodal biometric recognition system [2]. Then the feature extraction stage comes with different techniques, but some of the case feature calculation goes through a Hybridization approach.

We have divided our task into different sub-divisions. We select data for train, test and, validation in the data collection process. Where train division is used for train the model and validation division is used for how much accurately the model is training on train data. After that the test division is use for testing the model performance. Then we process data to fit the model. Then an augmentation is employed to the data during model fit. It helps to boost up to apply a generalization to the new data. After all, apply the artificial neural network model which is proposed by us. We use Convolutional Neural Network (CNN) model to build our proposed model and beside that some SOTA pre-trained model which also based on CNN model was applied for comparison study.

In this paper there are three more sections which are Backgrounds where literature review and related works describes, Research Methodology where all working procedure is described, Result and Discussion where all the outcome of our proposed models are discussed and compared, and Conclusion and Future Work where summary and future plan are described.

Chapter 2

Background

2.1 Related Works and Literature Review

In processing and recognizing is an efficient tool to work. This part of our paper will include some insight from the documents where different techniques have been applied to get the expected outputs.

Umer et al. [1] proposed identifying particular irises. Here the classification for feature learning is applied through Data augmentation. Some frequently used CNN architecture VGG16, ResNet50, Inception-V3 have been applied for feature extraction. The images used in the dataset are captured in a mixed (constrained, unconstrained) environment based on the lighting condition. Finally, The Border Count rank fusion technique improves Iris and particular recognition on the CASIA-dist. and UBIRIS.v2 database.

Image segmentation is a tool for partitioning the image to get the desired object or portion from that particular image fetching under consideration. Muhammad Arsalan and all [2] have chosen the iris segmentation approach for iris recognition. In Such kind of recognition system, the challenge is the environment. It is not possible to collect image data from a controlled environment all the time. So, the best practice will be to consider an unconstrained environment.

In the case of complex images, including an extra layer in the neural network provides more stability in the image-related task. Sometimes the accuracy rate falls due to adding additional layers into the network. Considering this type of scenario, such as iris recognition, where the feature extraction and accuracy are parallel monumental, Residual Convolutional Neural Network comes as a solution, used by Minaee et al. [3]. Transfer learning and pre-trained ResNet50 CNN architecture has been applied, and the approach proposed by the authors has given 95.9% accuracy.

Behera et al. [4] identify the maturity status of Papaya fruits. In this task, authors have applied transfer learning and machine learning. Both approaches reach the highest accuracy rate than the previously proposed methods. The privileged point behind the accuracy is the data collection method. All the image data used here are captured in a well-controlled environment that mitigates the complexity of the segmentation-related task.

Grassmann et al. [20] used color fundus pictures to predict Age-Related Macular Degeneration. A total of 13 classes were considered in this dataset (9 ARED, 3 late AMD, 1 upgradable images). Lighting change (brightness) and incident angle of the fundus camera can affect accuracy and internal operation in this type of prediction task. In order to ensure equal illumination and optimum lighting balance, the image collection is normalized in the preprocessing stage. After preprocessing the images, custom weighted k metric was applied, followed by pre-trained CNN architectures.

Segmentation is a key preprocessing step in the Iris identification challenge, and it can be accomplished using one of four approaches: (1) boundary detection (the most popular form), (2) pixel, (3) active contours and circle fitting, and (4) learning. Liu et al. [21] used the Hough Transform method to detect the iris curve, then used three fuzzy filters to minimize noise and enhance the image. The dataset was then subjected to CNN. The convolution layer extracts features in the CNN, while the pooling layer decreases the dimension derived from the convolution layer and prevents overfitting. It's worth noting that fuzzified picture filtering improves the efficiency of dataset training.

In [22], Silva et al. established a deep image representation-based approach for detecting contact lenses. A combination of Convolution neural networks and fully connected neural networks were utilized to overcome the difficulty of deep picture representation and categorization. During the training phase, an initial learning rate (LR) was set and trained on 100% data in four batches, with the fourth batch being chosen for validation. For accuracy measurement, a trained network architecture was used.

For contact lens detection, the Densely Connected Contact Lens Detection Network (DCLNet) was introduced in [23], which uses Customized DenseNet and SVM as feature extractor and classifier, respectively. Deep learning tasks necessitate a huge amount of data for feature extraction, which is necessary for training. The optimizer Stochastic Gradient Descent (SGD) with momentum has been used. Finally, DCLNet has been applied to a variety of datasets, showing excellent results with both normalized (89%) and degraded data sets. The accuracy of the non-normalized dataset (92 percent) is substantially superior.

Chapter 3

Research Methodology

This part will describe the instrumentation used, the data collection procedure, data analysis, and the proposed model. We use the deep learning classification method for our proposed work. We applied a multi-layer Convolutional Neural Network (CNN) [5-7] for this classification. This proposed model classified six different human iris colors.

3.1. Data collection

For this proposed work, we collected a total of 2705 data from numerous websites regarding iris color. Besides that, for some classes, we collected raw data from the relatives of the authors and known people. Table 1 demonstrates the categories, sources of data, and samples.

Figure 1: Workflow diagram.

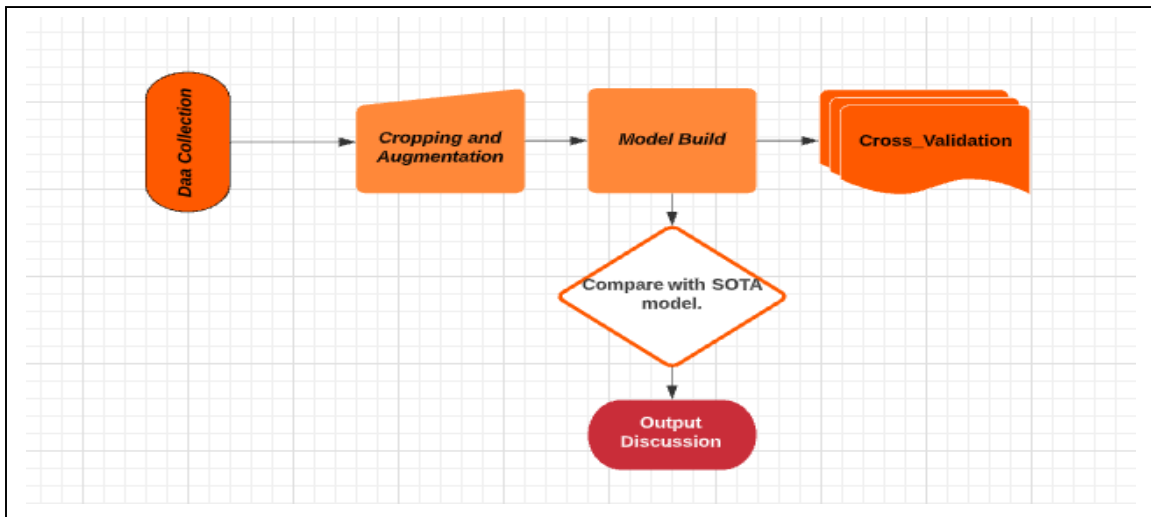
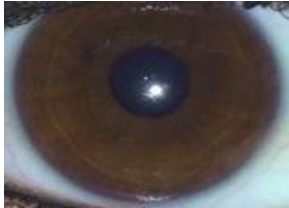
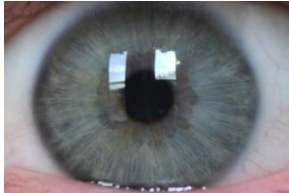


Table 1: Data types, Data collection sources, Quantities, and Samples.

Name	Sources	Quantity	Sample
Amber	Websites, Raw	410	
Blue	Websites	480	
Brown	Websites, Raw	510	
Gray	Websites	410	
Green	Websites	445	
Heterochromia	Websites	450	

3.2. Data preprocessing

After collecting the data, we distribute all of the data in a train, validation, and test folder, represented in table 2. Before dispersing, we cropped the data and took only the eye portion. Because when the data feed into the mode, it will only learn those features that it needs. It will also learn the other facial features like nose, leap, eyebrow, etc. Then our model also learns a lot of extra features unrelated to our work, and that underfitting problem will occur.

Table 2: Distribution of Data set.

Train	Validation	Test
2123	472	110

3.2.1. Augmentation

The augmentation procedures can create various images to improve the fit models' ability to generalize what they've learned to new images. We used the “ImageDataGenerator” [8] function, which is in the Keras [9, 10] framework. In table 3, the arguments of the “ImageDataGenerator” function are described.

Table 3: Functions Arguments with value/parameters.

Arguments Name	Value/Parameters
rescale	1./255
shear_range	0.2
zoom_range	0.2
horizontal_flip	True
vertical_flip	True
featurewise_center	True
channel_shift_range	0.2
fill_mode	'nearest'

This section of the preprocessing will generate a huge number of photos for training, validation, and testing. To allow the model to train on additional data, all of the arguments in table 3 were applied to the training data set. However, we only employ the first argumentation strategy from table 3 for validation and testing. The total amount of data that our proposed effort would generate is indicated in table 4.

Table 4: Total amount of data after using the “ImageDataGenerator” function for the proposed model.

Name of the domain folder	Function Arguments	Quantity of generated data	Total Data
Train	8	$2123 * 8 = 16984$	$16984 + 2123 = 19107$
Validation	1	$472 * 1 = 472$	$472 + 472 = 944$
Test	1	$110 * 1 = 110$	$110 + 110 = 220$

3.3. Data Analysis

From table 1, it's noticeable that each class has the image of one portion of the eyes, but for the Heterochromia class, we took both portions of the eyes. Heterochromia is a variety in coloration. The term is most frequently utilized to describe the color contrasts of the iris. Heterochromia is decided by the concentration of melanin [11, 12]. People with total heterochromia have eyes that are of diverse colors. That's, one eye may be green and their other eye brown, blue, or another color. If we divided it into the different classes, then the color will also be divided; for example, one portion can be Amber, or another portion can be Blue, which is separately recognized as Amber and Blue. And we already have these two different classes. That means it will conflict with another category. For this complexity reduction, we took both portions of the eye together so that our model could learn appropriately.

3.4. Proposed CNN Model

In deep learning, CNN is most commonly used for medical image analysis, image classification, and video classification. Working with the CNN model needs a lot of data and is also expensive in device specification and equipment [12]. We took three convolutional layers and two fully connected layers for our model, represented in table 5.

Table 5: All the hyper parameters of our proposed model.

Layers	conv2d_1	maxpool_1	conv2d_2	maxpool_2	conv2d_3	maxpool_3	FC1	FC2
Kernel	3*3	2*2	3*3	2*2	3*3	2*2	-	-
Channel	32	32	32	32	64	64	128	6
Activation Function	'relu'	-	'relu'	-	'relu'	-	'relu'	'softmax'

At first, create three convolution layers, which take features from images and create feature maps. After constructing the feature map, max-pooling reduces the image size. Because our data collection comprises photos in various formats, the input shape of the image is set to (150, 150, 3), which resizes the image. The second and third convolution layers are similar to the first convolutional layer, with a few exceptions. The size of the filter for extracting features is larger than the previous layer, 64 for both, respectively. The feature maps are then flattened to convert the CNN's convolutional part into a 1D include vector-like classifier. The final stage of the CNN model sense layer classifiers, an associated dense layer. In figure 2, the proposed model is demonstrated, and in table 6, the parameters we selected for our model are shown.

Figure 2: Our proposed CNN Model structure.

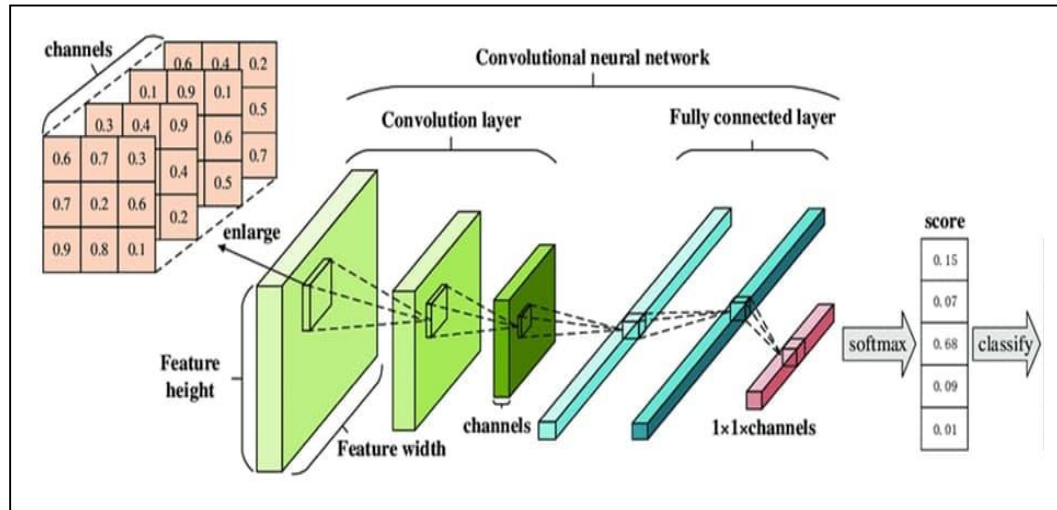


Table 6: All the parameters of our proposed model.

Parameter Name	Parameter Argument
Epoch	30
Verbose	2
Optimizer=Adam(learning rate)	0.0001
Loss	'categorical_crossentropy'
Metrics	'accuracy'

3.5. Cross-validation

We used stratified cross-validation to assess the performance of our deep learning model. To find the most refined collection of hyperparameters, cross-validation is used. For a given set of hyperparameters and data, the optimizer finds the best set of parameters, such as gradient descent, adam, and so on. We assessed every fold result using 'n split = 3' and 'epoch = 10' and compared it to our proposed approach.

3.6. Transfer Learning

Transfer learning is a machine learning method in which a model for the help task is built from an actual demonstration. Transferring data from a previously taught related work to facilitate learning in a new task is what it implies. Transfer learning is an optimization that enables for rapid advanced execution while modeling the second task [13]. To classify all of the classes chosen for categorization, this work employs a cutting-edge model. Before applying the model to our data collection, we tweaked the model's preprocessing component. The preprocessing method established for the state-of-the-art model was used. We utilize 'ResNetV2' [14] to classify all classes. Apart from that, we supplemented with 'inceptionResNetv2' [15]. Table 7 shows the following parameters and hyperparameters for this model.

Table 7: Name of the Arguments of Transfer Learning Model.

Name of the Arguments	Parameter/hyperparameter value
Epoch	5
Verbose	2
Trainable Parameter	54,285,414
Non-Trainable Parameter	60,544

Chapter 4

Result & Discussion

This section will describe our proposed model and explore the discussion that occurs. We used “Google Colab” to execute the experimental results. Figure 3 shows the results of our proposed model's examination. The maximum and minimum values of loss and validation loss are 1.55 and 0.41, respectively, and val_loss is 1.32 and 0.48. In terms of accuracy and validation accuracy, the top and lowest values are accuracy 0.84 and 0.39, respectively, and val_accuracy 0.81 and 0.45. Aside from that, there is no overfitting or underfitting in our model [16, 17]. We employ stratified cross-validation with three splits to cross-check our suggested model classification result. Table 8 displays the loss and accuracy of each split.

Figure 3: Proposed model Evaluation.

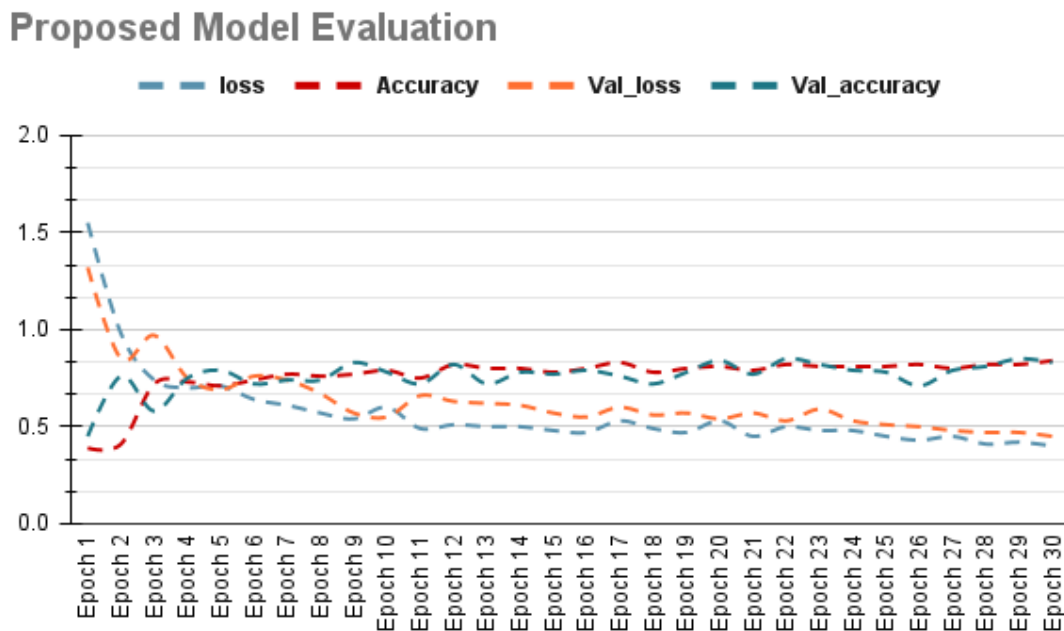
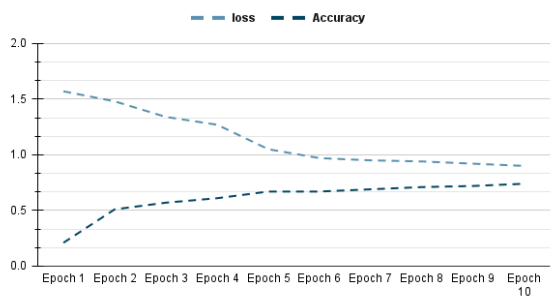
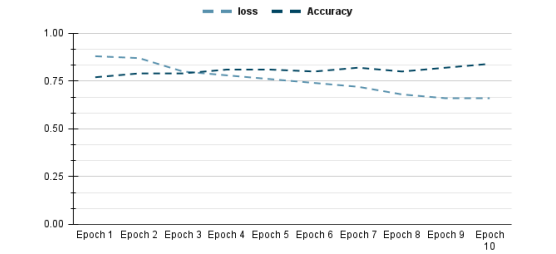
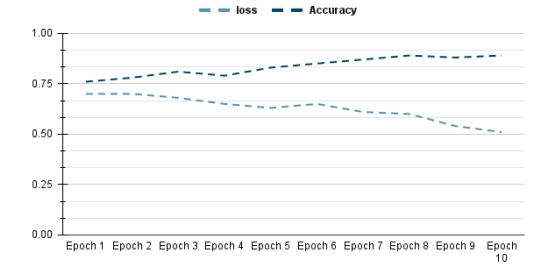


Table 8: Cross-validation performance for each split.

n_split = 1	Split_1  <table><thead><tr><th>Epoch</th><th>loss</th><th>Accuracy</th></tr></thead><tbody><tr><td>Epoch 1</td><td>1.6</td><td>0.2</td></tr><tr><td>Epoch 2</td><td>1.5</td><td>0.5</td></tr><tr><td>Epoch 3</td><td>1.4</td><td>0.55</td></tr><tr><td>Epoch 4</td><td>1.3</td><td>0.6</td></tr><tr><td>Epoch 5</td><td>1.1</td><td>0.65</td></tr><tr><td>Epoch 6</td><td>1.0</td><td>0.68</td></tr><tr><td>Epoch 7</td><td>0.95</td><td>0.7</td></tr><tr><td>Epoch 8</td><td>0.9</td><td>0.72</td></tr><tr><td>Epoch 9</td><td>0.88</td><td>0.74</td></tr><tr><td>Epoch 10</td><td>0.9</td><td>0.75</td></tr></tbody></table>	Epoch	loss	Accuracy	Epoch 1	1.6	0.2	Epoch 2	1.5	0.5	Epoch 3	1.4	0.55	Epoch 4	1.3	0.6	Epoch 5	1.1	0.65	Epoch 6	1.0	0.68	Epoch 7	0.95	0.7	Epoch 8	0.9	0.72	Epoch 9	0.88	0.74	Epoch 10	0.9	0.75
Epoch	loss	Accuracy																																
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n_split = 2	Split_2  <table><thead><tr><th>Epoch</th><th>loss</th><th>Accuracy</th></tr></thead><tbody><tr><td>Epoch 1</td><td>0.9</td><td>0.75</td></tr><tr><td>Epoch 2</td><td>0.85</td><td>0.78</td></tr><tr><td>Epoch 3</td><td>0.8</td><td>0.8</td></tr><tr><td>Epoch 4</td><td>0.8</td><td>0.8</td></tr><tr><td>Epoch 5</td><td>0.75</td><td>0.82</td></tr><tr><td>Epoch 6</td><td>0.75</td><td>0.82</td></tr><tr><td>Epoch 7</td><td>0.7</td><td>0.83</td></tr><tr><td>Epoch 8</td><td>0.65</td><td>0.82</td></tr><tr><td>Epoch 9</td><td>0.65</td><td>0.85</td></tr><tr><td>Epoch 10</td><td>0.65</td><td>0.85</td></tr></tbody></table>	Epoch	loss	Accuracy	Epoch 1	0.9	0.75	Epoch 2	0.85	0.78	Epoch 3	0.8	0.8	Epoch 4	0.8	0.8	Epoch 5	0.75	0.82	Epoch 6	0.75	0.82	Epoch 7	0.7	0.83	Epoch 8	0.65	0.82	Epoch 9	0.65	0.85	Epoch 10	0.65	0.85
Epoch	loss	Accuracy																																
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n_split = 3	Split_3  <table><thead><tr><th>Epoch</th><th>loss</th><th>Accuracy</th></tr></thead><tbody><tr><td>Epoch 1</td><td>0.7</td><td>0.75</td></tr><tr><td>Epoch 2</td><td>0.68</td><td>0.78</td></tr><tr><td>Epoch 3</td><td>0.65</td><td>0.8</td></tr><tr><td>Epoch 4</td><td>0.65</td><td>0.78</td></tr><tr><td>Epoch 5</td><td>0.62</td><td>0.82</td></tr><tr><td>Epoch 6</td><td>0.65</td><td>0.85</td></tr><tr><td>Epoch 7</td><td>0.6</td><td>0.88</td></tr><tr><td>Epoch 8</td><td>0.58</td><td>0.9</td></tr><tr><td>Epoch 9</td><td>0.52</td><td>0.9</td></tr><tr><td>Epoch 10</td><td>0.5</td><td>0.9</td></tr></tbody></table>	Epoch	loss	Accuracy	Epoch 1	0.7	0.75	Epoch 2	0.68	0.78	Epoch 3	0.65	0.8	Epoch 4	0.65	0.78	Epoch 5	0.62	0.82	Epoch 6	0.65	0.85	Epoch 7	0.6	0.88	Epoch 8	0.58	0.9	Epoch 9	0.52	0.9	Epoch 10	0.5	0.9
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Tables 9 and 10 demonstrated the proposed model's accuracy, precision, and f1 score and each split of cross-validation. We tested the proposed model on 110 unseen data and cross-validation on 369 unseen data. We observed that the proposed model performs nicely from these tables though the accuracy result is almost similar.

Table 9: Classification report of Proposed Model.

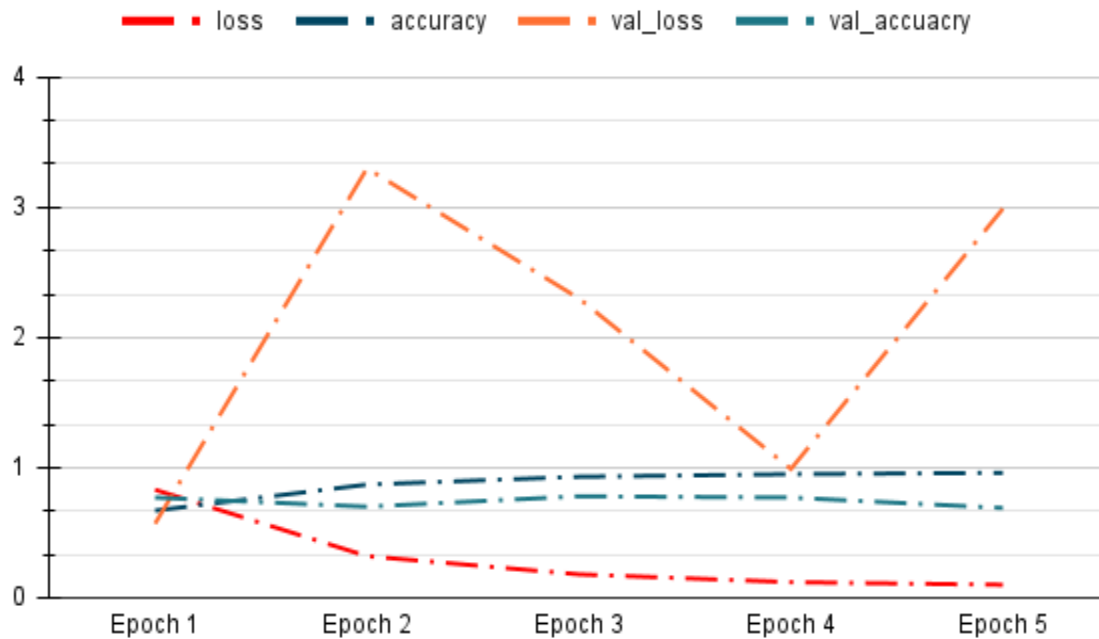
Name	Precision	F1 Score	Accuracy
Amber	75.0%	77.0%	90%
Blue	1.0%	1.0%	
Brown	81.0%	83.0%	
Gray	90.0%	90.0%	
Green	94.0%	89.0%	
Heterochromia	1.0%	1.0%	

Table 10: Classification report of Cross-validation.

Name	Precision	F1 Score	Accuracy
n_split = 1	80.8%	78.4%	79.1%
n_split= 2	86.3%	85.7%	86.1%
n_split = 3	88.7%	88.7%	90.6%

Figure 4: Model evaluation of “ResNetV2” Transfer Learning Model.

ResNetV2



Here, table 9 found that in split_3, the accuracy is 90.6, which is quite similar to table 8 accuracy. On the other hand, the model evaluation for 'ResNetV2' is shown in Figure 4. From this evaluation, we found that val_loss fluctuates, which means the model can't validate on validation data set correctly. Besides that, the highest value for accuracy of training accuracy is 0.9656, val_accuracy is 0.6928, and the lowest value for loss and val_loss is 0.1053 and 2.99. It is clear that the underfitting problem occurs for this model. After model evaluation, we tested on 110 unseen data where this model was able to predict with 74.55% accurately, and the misclass was 25.45%.

After evaluating both our proposed CNN model and the Transfer learning model, it is clear that our proposed CNN model is working better from both models. So, our model can use it for solving real-world problems.

Chapter 5

Conclusion and Future Work

This paper describes how to use a classifier system to learn the color of human iris photos. Deep learning was used to train the classifier in this application, which consisted of 2123 photos. This type of learning, specifically the convolutional neural network for image data categorization, is the focus of our research. In addition, ResNetV2 should be used in conjunction with the transfer learning technique. We have demonstrated that our suggested model outperforms the current Transfer Learning model. Fine-tuning parameters, also known as transfer learning [18], is a common and effective training approach for improving model performance in general. However, while this fine-tuning yielded acceptable results and saved training time, it fell short of our suggested model.

Since the training period, overfitting, and underfitting can all be adjusted, deep learning is crucial. In future investigations, evolutionary algorithms will be used to optimize and solve the classification feature extraction problem, reducing the number of parameters. Aside from that, we'll add more data and apply some more preprocessing approaches to strengthen our model. A comparative study employing different state-of-the-art Transfer Learning models is also conducted.

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