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Classification of Multiple Visual Field Defects using Deep Learning

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Abstract. In this work, a custom deep learning method is proposed to develop a detection of visual fields defects which are the markers for serious optic pathway disease. Convolutional Neural Networks (CNN) is a deep learning method that is mostly used in images processing. Therefore, a custom 10 layers of CNN algorithm is built to detect the visual field defect. In this work, 1200 visual field defect images acquired from the Humphrey Field Analyzer 24–2 collected from Google Image have been used to classify 6 types of visual field defect. The defect patterns are including defects at central scotoma, right/left/upper/lower quadratopia, right/left hemianopia, vision tunnel, superior/inferior field defect and normal as baseline. The custom designed CNN is trained to discriminate between defect patterns in visual field images. In the proposed method, a mechanism of pre-processing is included to improve the classification of visual field defects. Then, the 6 visual field defect patterns are detected using a convolutional neural network. The dataset is evaluated using 5-fold cross-validation. The results of this work have shown that the proposed algorithm achieved a high classification rate with 96%. As comparison, traditional machine learning Support Vector Machine (SVM) and Classical Neural Network (NN) is chose and obtained classification rate at 74.54% and 90.72%.

1. Introduction

The visual field test is a technique of measuring an individual's entire scope of vision to screen peripheral vision loss and optic nerve condition. The vision loss or defect inside human's visual field can be an indicator to various optic pathway illness where in the worst-case scenario can be a marker of more serious illness such as a tumor, stroke or optic neuropathy. These can be determined based on site, size, and margin of the vision loss from visual field images. Most of the previous work used visual field defect patterns to detect certain types of optic pathway disease and most of them usually focus on specific diseases such as glaucoma [1] or diabetic retinopathy [2][3][4].

World Health Organization (WHO) had stated that in 2018, about 2.6% of death occurs for brain and nervous system problem in Malaysia. The organization also stated that in 2017, there are more than 50% of Malaysian have high risk to get stroke attack and some of them need to undergoes any drug therapy and counselling to prevent it [5]. In 2014, WHO stated that 3% from Malaysian have diabetes at ages 18 years old and above [5]. The Global Cancer Organization had recorded that about 14.5% of population in Malaysian are risk of developing cancer before the age of 75 years and 8.8% are risk of dying from cancer before the age of 75 years. There are 2.6% from risk of dying is from brain and nervous system cancer [6]. These life-threaten illnesses can be detected early by simply performing a visual field test to identify any vision loss which can lead to early diagnosis.

In this work, the visual field images will be classified into 6 different types of visual field defects which can be used to recognize a few optic pathway diseases. The first pattern is right/left homonymous hemianopia, which is an indicator of brain tumor, stroke, hemorrhage, and pus collection. The defect area shows in this image is on both the right sides of the eyes. The second pattern is right/left upper/lower quadratopia, which is an indicator of brain tumor, stroke, hemorrhage, plus collection around the temporal and parietal area of the brain. The defect shows on the left side at the upper part on both eyes. The third is the superior/inferior defect field, it is an indicator of retinal detachment, eye tumor. The defect shows are on the quarter upper part or lower part of the eyes. The fourth pattern is central scotoma which is a high risk to get central macula problems. The defect shows are big dots and small dots at the center on the right or left of the eyes. Fifth is tunnel vision, which is a high risk to get glaucoma. The defect shows are all part of the eyes accept at the center of the eyes. Lastly, the normal visual field also will be included.

Deep learning is a sophisticate machine learning algorithm that is usually used in neural networks for training and prediction of datasets [7][8] and it prevent the researcher to figuring out most predictive features directly from the large dataset [2][9]. Feature extraction from a pre-trained deep learning model performs well on a variety of tasks including tasks that differ greatly from the first task that the feature extractors were trained [10] and as the number of samples and parameters the increasing, the artificial selection significantly limited production classification. Hence, deep learning will automatically search for the most notable features from thousands of parameters [11].

Neural network methods have achieved excellent result in many application of computer vision in recent years, especially in medical application. Recently, convolutional neural networks have achieved cutting-edge efficiency on a number of artificial intelligence task [12]. The feature extraction and classification tasks can be optimized jointly. In the diagnosis of certain disease, the convolutional neural networks have also been successfully used, which involves mostly imaging reporting. Along with the convolutional neural network, which successfully in image recognition [13].

Therefore, in this work, a custom CNN is used to detect optic pathway disease from visual field defect pattern. CNN is a deep learning algorithm that can capture image input, attribute learning weights and biases to different aspects or objects in the image, and distinguish between them. This approach is commonly utilized to solve complex problems. It does away with the limitations of traditional machine learning approaches [14].

2. Literature Review

Several methods to detect disease from visual field had been proposed especially glaucoma detection. For machine learning classifier, 999 visual field images as their dataset had been used by Yousefi *et al*. (2016) and Yousefi *et al*. (2014) [15][16]. Gaussian Mixture Model with Expectation Maximization and Variational Bayesian Independent Components Analysis Mixture Model to cluster the dataset had been compared and obtained the specificity and sensitivity. They obtained 89.9% specificity and 93.8% sensitivity for Gaussian and 93.0% specificity and 97.0% sensitivity for Variational Bayesian. Goldbaum *et al*. (2012) also used the Variational Bayesian Independent Mixture Model (VIM) to detect the detection of glaucoma with a set of 2085 visual field eyes. The accuracy was 93.5% [17]. Wang *et al*. (2019) used Bayesian Information Criterion (BIC) method to identify 13,951 Humprey

Visual Field 10-2 dataset taken from 8712 patients [18]. The accuracy obtained is 95%. Gardenial *et al*. (2017) using the clustering method accuracy obtained is 95%.

Besides using machine learning classifier, there are also some researchers using deep learning methods to detect glaucoma from the visual field defect. Kucur *et al*. (2019) used Convolution Neural Network to detect Humphrey Field Analyzer 24-2 and OCTOPUS 101 G1 dataset [19]. The accuracy obtained is 84.5% for OCTOPUS 101 G1 dataset and 98.5% for Humphrey Field Analyzer 24-2 dataset. *Li et al.* (2018) also used the Convolutional Neural Network method to detect 4012 eye images and the accuracy obtained 87.6% [12]. Park *et al.*, (2019) also using deep learning method the Recurrent Neural Network and the accuracy obtained 88% [13]. There also other deep learning method had been used by Berchuck *et al.*, (2019).

Most of previous works were experimenting and performing detection against different types of optic pathway diseases. Many of them used the visual field image to detect vision loss caused by a specific disease such as glaucoma and diabetic retinopathy. In contrast, our work focus on wider scope where the detection of 6 types of visual field defects are observed to distinguish more types of optic pathway illness. For Kucur *et al*., (2019) the accuracy is higher than this work because it detects 2 classes of disease while this work detects 6 classes of diseases.

3. Methodology

This section will discuss proposed method for this work. First, 1200 visual field defect images are collected from Google Image. Then, the dataset feature will undergo pre-processing and classification using a convolutional neural network in the deep learning mechanism. Finally, evaluation is done by using 5-fold cross-validation to measure the accuracy of the detection.

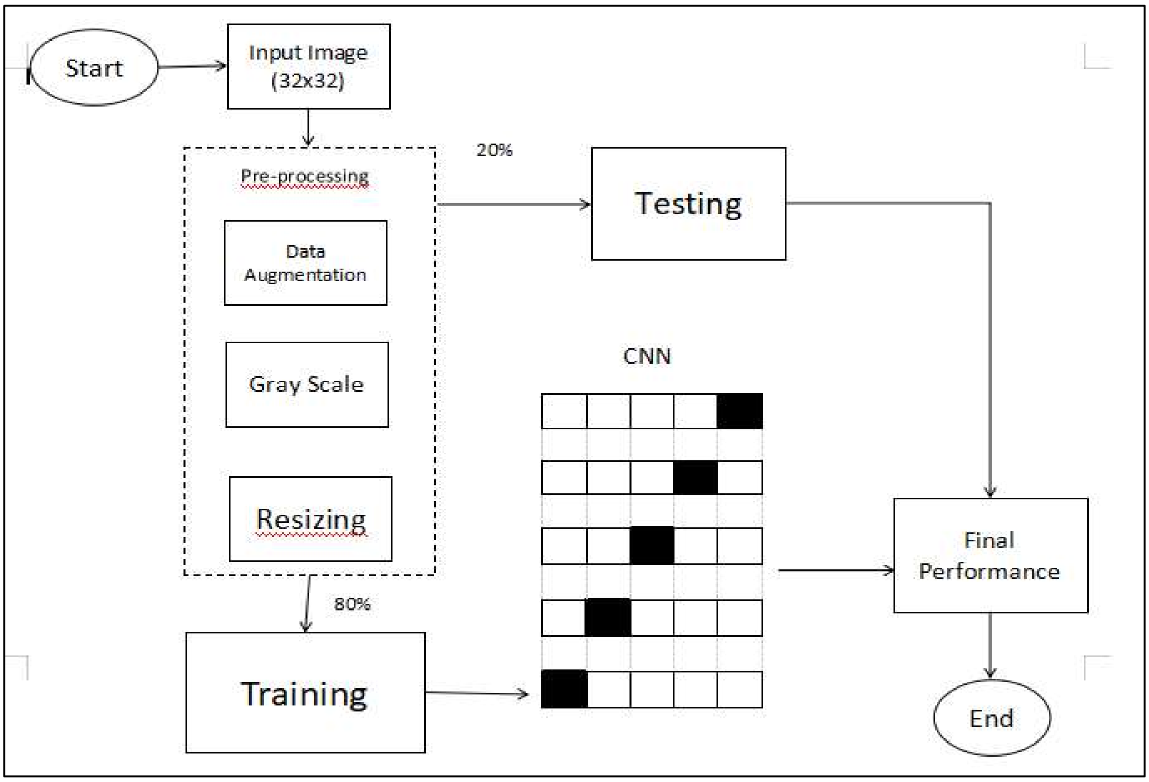


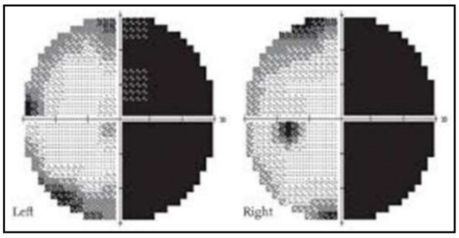
Figure 1. Flowchart Visual Field Defect Classification

3.1. Data Collection

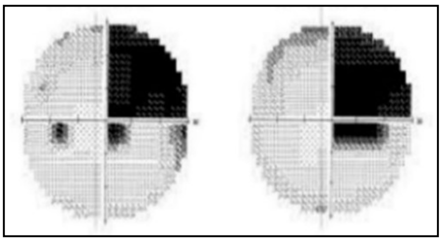
This work begins with data collection of 1200 visual field images from Google Images most of the images are download from medical report and crop and divided into six folder based on it classes, 200 images for each classes. The images will be trained in Convolutional Neural Network to extract the feature map in the images. This work focus on classification of 6 types of visual field defect images. The information for visual field defect pattern and the disease detected from the pattern are:

- Right /left homonymous hemianopia which is an indicator brain tumor, stroke, hemorrhage, plus collection respecting the vertical line.
- Right/ left/upper/lower quandratopia which is an indicator brain tumor, stroke, hemorrhage, plus collection around the temporal and parietal area of brain respecting the vertical line.
- Superior/inferior field defect which is an indicator retinal detachment, eye tumor not respecting vertical line.
- Central scotoma to detect central macula problems.
- Tunnel vision to detect glaucoma.
- Normal visual fields images.

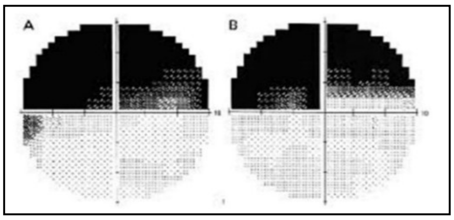
The example of the defect pattern of visual field defect is shown in the figure below:



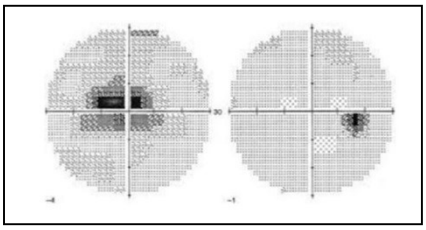
Right /left homonymous hemianopia



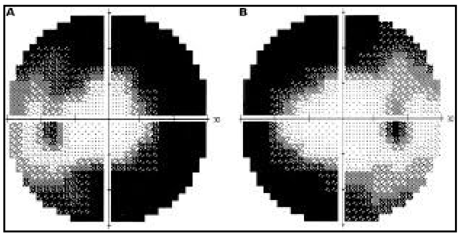
Right/ left/upper/lower quandratopia



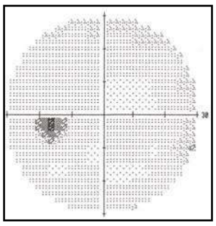
Superior/inferior field defect



Central Scotoma



Vision Tunnel



Normal

Figure 2. Example of visual field defect

3.2. Pre-Processing

Pre-processing one of the important steps in image classification that can be used to enhance the accuracy of image classification if there any different quality of the images use. Therefore, several techniques are applied in this work to improve the accuracy of classification.

First, the data augmentation method is applied to widen the heterogeneity of images, but prognostic features are kept within the image itself because the original images contain many physiological information of patients [20]. The data augmentation will improve the performance of training model by increase the number of datasets. In data augmentation, the collected image will be split into left and right eye so the datasets should be noted for the left eye or right eye because the defect pattern is different.

Then, the visual field images are resized into a 32 × 32 color image. Resizing is a process to resize all datasets into the same size by choosing suitable pixels for the dataset. This step is important to determine a base size for all datasets before setting up the algorithm [21][22]. During resizing process, the text noted on the visual field will be crop out.

Lastly, the visual field images are converted into a greyscale channel so the quality and information from the original image is improved as much as possible [23]. Based on maximum entropy theory determines the optimal gray level classification threshold of the image using the iterative algorithm, and the transforming function performs the local the grey level transform function. The equation is as follows equation (1) [11] [20]:

$$H(x) = \sum_{i=1}^{k} p(x = x_1) log \frac{1}{p(x=x_1)} \tag{1}$$

3.3. Convolutional Neural Network (CNN) Modelling

In this work, a custom convolution neural network is going to be accustomed to perform a deep learning modelling. The input data will undergo 10 layers of convolutional and sub-sampling process that produce several layers of feature maps. Convolutional layers apply several filters to the input data while sub-sampling layers reduce the input data size. Max pooling, stochastic pooling, and average pooling are going to be considered during sub-sampling. For training and classification, the final layer of convolutional or sub-sampling layer is linked to a fully connected neural networks. The detail of deep convolutional neural network parameter is explained below:

In custom convolutional neural network, convolutional layers are accustomed study the small feature detectors supported by patches randomly sampled from a large dataset. A feature in some location from the visual field image is calculated by convolving the feature detector [24]. The input shape for first layer of convolutional layer is 32 × 32 color images. The image is then transmitted through a stack of convolutional layer, where the filters were used with small receptive fields: 2 × 2 and 3 × 3, which is the smallest size for capturing the notion of right and left, down and up and visual field defects center [24]. Figure 3, shows the example of convolutional neural network layers framework.

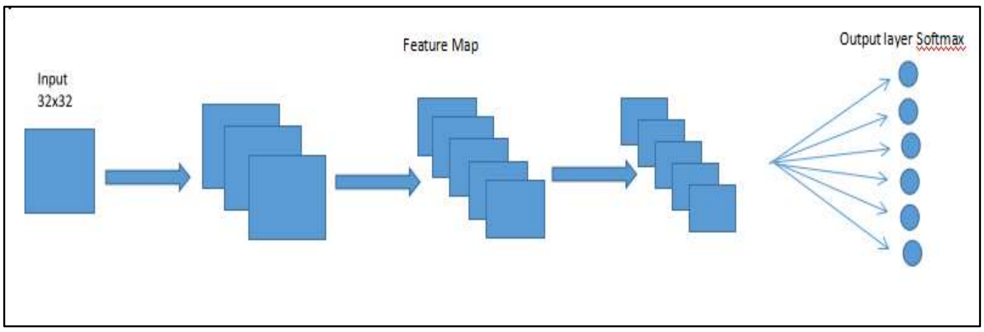


Figure 3 . Framework of Convolutional Neural Network

In this work, max pooling layer is come after the convolutional layers to decrease the dimensions of the feature maps (some convolutional layer followed by average pooling). Max pooling layers have generalizing capabilities and makes the representation invariant of minor inputs translation. An image is separated by each into sets of non-overlapping rectangles. Then some calculation is performed, depends on the operation types, e.g. in Max Pooling layer the highest values from rectangles are taken to produce the output feature [25]. Max pooling layer decrease the amount of parameters to be calculated and provides essential invariance of the translation into interior representation, while also reducing the computational costs [26]

Dropout layer also adds in this custom convolutional neural network to performs cheap and powerful operation that greatly enhances the neural network generalization capabilities [25]. This layer includes the random removal and regeneration of neurons during the training process, with a probability calculated by the hyper-parameter called dropout rate [25]. This layer is used in this proposed design to avoid overfitting by avoiding the network from depending on single node inside the layer [26]. This layer also helps to cut back fluctuation in model accuracy graph.

As in the previous row, some fully connected layer neurons connect with the previous layer to all the neurons. These layers are used as a final element of deep neural classifier. The last layer producing a Softmax layer for multi-class resolution task on the network weather output or sigmoid neuron for binary resolution task [25] It is the high-level reasoning inside the neural network after multiple convolutional and max pooling layers have been carried out fully connected layers [26]. In this work, the solving task is multi class so Softmax layer is used within the last layer.

Lastly, the activation function is parameter have to be tune to enhance the performance of deep learning. The activation functions that often utilized in deep learning are ReLU, Tanh, and Sigmoid. The activation function is added within the layer of deep leaning to feature nonlinearity after each layer, without the entire network that acts as an easy linear transformation. It has not got much power to do complicated tasks like classification of images [26]. ReLU was used as activation function to train the deep neural network efficiency in comparison to sigmoid and regression activation functions [26]. Besides that, the parameter in deep learning also are going to be tune based on the dataset used. Therefore, ReLU function is employed in convolutional layer of this work because the visual field images are positive solving task.

The other parameter needs to be tune to improve deep learning performance of it hyper-parameter. The deep learning hyper-parameter also included optimizer, epoch, and batch size. The regularization, the learning rate, and the number of nodes for each hidden layers are the key factors that affecting the performance of the algorithm. Therefore, parameters tuning deep learning is done [26]. For the hyper-parameter the optimizer used is SGD and 50 epochs, with 32 batch size is used.

SGD optimizer is used because it is used to train algorithm that most notably neural network in deep learning. It is to find a collection of internal model parameters that function well against certain output [27]. The number of epoch and batch sizes, the number of epochs is traditionally large, often hundreds or thousands, enabling the learning algorithm to run until the model error has been minimized enough [27]. Each sample of epoch is to update the internal model parameters. Therefore, this work stops at 50 epochs because it had shown high accuracy. 32 batch size is chosen because it is most frequently used by previous researcher.

3.4. Traditional Methods

As a comparison, this work is also evaluated in traditional machine learning method for 6 class of visual field defect. In addition, traditional machine learning is compared with this work method. The traditional machine learning methods that chose to compare with the proposed work are Support vector Machine (SVM) and Classical Neural Network (NN).

Support vector Machine (SVM): A high dimensional points training samples is maps by SVM, which can be separated by a hyperplane as widely as possible [28]. SVM is a linear model for problems with the regression and classification. This can solve both non-linear and linear issues and working well on other practical issues [29]. SVM algorithm creates a hyperplane or line to divide dataset into several classes. By mapping data of interest into a much higher dimensional space before a decision surface is found SVM can isolate dataset that hard to separate in the original data space and allows the input data to be divided into six classes of visual field defects: central scotoma, right/left/upper/lower quadratopia, right/left hemianopia, vision tunnel, superior/inferior field defect, and normal.

For tuning the parameter in SVM. Gamma is used because it determines how much a single example of training exerts its impact. If each point has a wide range means the gamma has low value and if each point has close reach means the gamma has conversely high value. If gamma has a very high value, then the boundary of the decision will depend on the points that are very close to the line resulting in ignoring some of the points that are very far from the boundary of the decision. It is because the closer points are having more weight and resulting in a wiggly curve as seen in the graph above. On the other hand, even the distant points get considerable weight if the gamma value is low, and more linear curve can be obtained [29].

Classical Neural Network (NN): The basic architecture of classical NN must contain three layers: Input layer, hidden layer and output layer. The function of each layers of classical NN, the differences is classical NN only has 3 layers and CNN has several layers of NN. The activation function of output layer in NN is very important in order to define the type of model to achieve either classification or regression. In this work, Softmax activation function is used to classified multiclass input data. If one hidden layer that composed of two nodes will end up with a dimensionality vector of weights. This puts the training challenging in perspective as the number of nodes increases. Operation are linear combinations, except for the activation functions because it introduce non-linearity [30]

4. Result and Discussion

The detection of optic pathway disease from the visual field algorithm will be written in python interphase because python is suitable for a robust programming language that has its main focus on rapid application development. The packages used to develop this system is Keras-Sequential (Tensorflow backend). Deep learning is the structure of several layers of neural networks. Therefore, high-performance GPU in Google Colab on Tesla K80 GPU and 64GB RAM is used to run a convolutional neural network.

4.1. Validation

K-fold cross-validation is a common form of cross-validation, used commonly in machine learning. This method used original images of visual field defects and partitioned it at random into 5 subsamples of equal size. As validation data for testing the model, a single subsample is maintained, and the remaining 5-1 subsamples are used as training data as show in the flowchart (Figure 1).

Both observations are used for the training process by using 5-fold cross-validation, and each observation is used exactly once for the validation process [31]. Therefore, 5-fold cross-validation will be used to process the visual field defect images dataset to obtain accuracy. The visual field defect dataset is divided into an 80:20 ratio as a training and testing dataset.

The performance of the proposed method will be assessed by using the following accuracy measurements:

$$\text{Sensitivity} = \frac{\text{Number of true positive}}{\text{(Number of true positive + false negative)}} \tag{2}$$

$$\text{Specificity} = \frac{\text{Number of true negative}}{\text{(Number of true negatives + false negative)}} \tag{3}$$

$$\text{Accuracy} = \frac{(\text{Number of correct predict image})}{(\text{Total number of tests image})} \quad (4)$$

4.2. Result

Before undergoes cross-validation, the testing datasets will be inverted from a white background and black visual field defect dataset into a black background and white visual field defect dataset so the prediction of visual field defect datasets are more accurate. Figure 9, shows accuracy obtained for each k-fold for 5-fold cross-validation in the convolutional neural network. From the figure, the accuracy for each 5-fold are almost the same if the accuracy range too far, there are some problem in that fold. The average accuracy of 5-fold cross validation of CNN is 96 %.

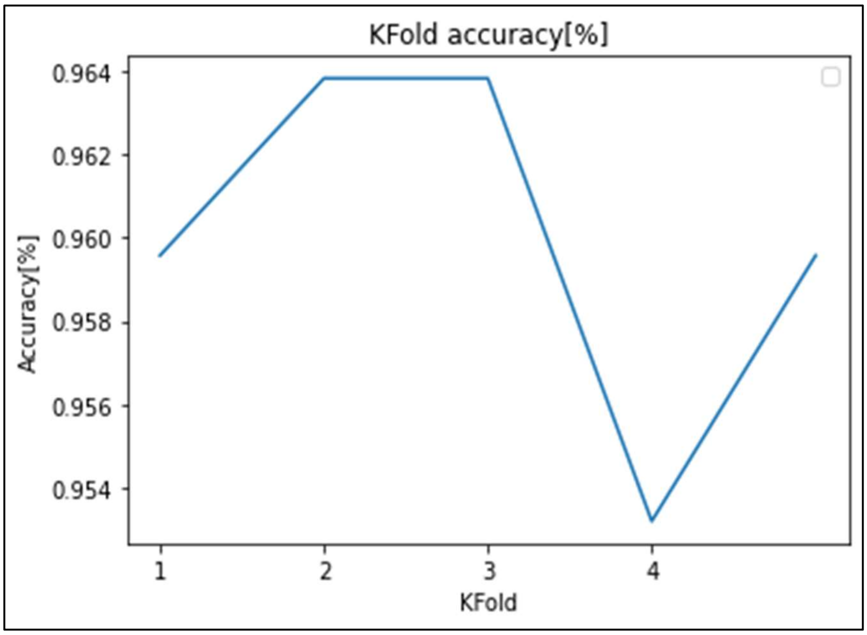


Figure 4. Accuracy for each CNN K-fold

This work also had been validate with SVM and classical NN as comparison. The average accuracy of 5-fold cross validation SVM is 74.54% and the average accuracy of 5-fold cross validation classical NN is 90.72%. The accuracy for both traditional machine learning is lower than CNN deep learning method. Table I, shows the average accuracy for each fold for both traditional machine learning and proposed work.

Table I. Accuracy

Methods	Accuracy (%)
Classical Neural Network	90.72
SVM	74.54
CNN (proposed work)	96.0

The accuracy obtained by visual field defects are above 90% for each class by using equation 4 for calculating the accuracy for each class of visual field defect datasets. The overall of six classes of visual field defect datasets shows the same accuracy of 5-fold validation so it is shown that the splitting between training datasets and testing datasets for 5-fold validation is the best fit. Table II shows the accuracy for each class.

Table II. Evaluation for each Visual Field Defect

Visual Field Defect	Accuracy (%)		
	NN	SVM	CNN (proposed work)
central scotoma	86	68	91
right/left/upper/lower quadratopia	99	73	98
right/left hemianopia	88	90	98
vision tunnel	93	85	100
superior/inferior field defect	89	82	92
Normal	85	79	97
Average Accuracy	90	79.5	96

The time taken for 5-fold is also recorded both in GPU and CPU in Google Colab. The time taken to classified the visual field in Google GPU is 61.73 s compared to using only CPU the time taken is 93.88 s which is longer than the time taken for GPU. This is because GPU has advance calculation ability that accelerates the amount of visual field defect datasets especially when the programs have complex mathematical calculation like deep learning. The time taken for SVM are both 23.58 s for both CPU and GP and time taken for Classical NN are 43.77 s when run on CPU and 77.29 s when run on GPU.

4.3. Discussion

A confusion matrix often used to define a classification model's output on a set of test data for which the true values are known. The confusion matrix itself is easy to understand, but the terminology associated with can be confusing [32]. '1', '2', '3', '4', '5', and '6' are six possible predicted classes labels in the confusion matrix. If the image were predicting '1', it would mean that the patient have central scotoma, if the image were predicting '2', it would mean that the patient have quadratopia, if the image were predicting '3', it would mean that the patient have hemianopia, if the image were predicting '4', it would mean that the patient have vision tunnel, if the image were predicting '5', it would mean that the patient have field defect, and if the image were predicting '6', it would mean that the patient have normal.

The confusion matrix of visual field defect classification shows that, the highest rate of classifications for visual field defect classification at 100% for vision tunnel and the lowest rate of classification at 91% with 8% error rate for central scotoma because the image of central scotoma almost similar to normal visual field defect cause the dataset detect normal instead of central scotoma. From the confusion matrix, 7% of error rate in central scotoma predict normal and 1% predict hemianopia.

For other visual defects, quadratopia has 98% classification rate with 2% error rate predict as tunnel vision defect. For hemianopia, its classification rate is 98% the same as quadratopia with error rate 2% predict as central scotoma. For field defect, the classification rate is 92% with 8% error rate 5% predict as central scotoma, 2% predict tunnel vision and 1% predict as normal visual field. Lastly, for normal visual field, it has 97% classification rate with 3% error rate predict as tunnel vision. Figure 5, shows the confusion matrix which is created to analyse the classification errors of the CNN model used in this work.

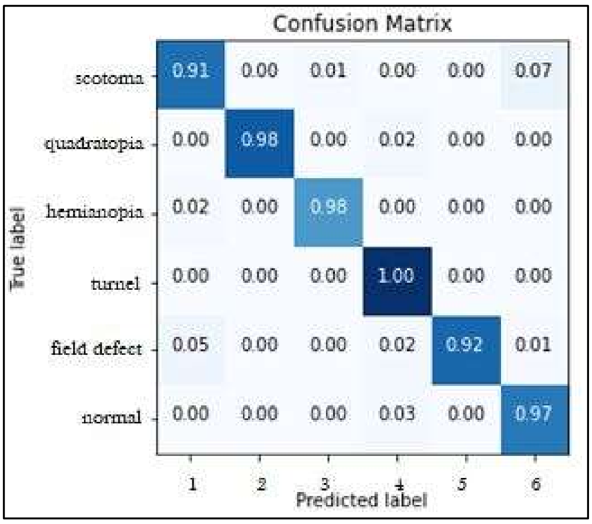


Figure 5. Confusion matrix of Visual Field Defects datasets

From the experiment, there are several differences of using traditional machine learning (SVM and classical NN) and deep learning (CNN). First is the computation power: A GPU that have thousands of cores is need to train deep learning network because it networks are data dependent. CPU is not recommended to be used for deep learning because it has limited cores. Computation power is needed especially on the large numbers of dataset data and large the network (more layers of deep learning networks, the larger the size of deep learning networks). Traditional machine learning algorithm could be implemented on CPU because it already has relatively good requirement [33].

Second differences is the time training and it inference time. For training time deep learning network, it can vary from a few hours to month. Besides the numbers of dataset and networks, the number of parameters known as weights would also may resulting in slow training. Deep learning can also take enough of inference time because the test data passes through the layers in the network, there will be a lot of multiplication which will take more of time. Although traditional machine learning algorithms are train faster than deep learning between few minutes to a few of hours, some algorithms may also take quite some time but during testing time [33]. The differences time between deep learning and traditional machine learning has been shows in above experiment that time taken for machine learning is faster than deep learning.

Lastly, to solve a problem by using machine learning methods, the problems need to be divided it have to divide into two parts: feature extraction and classification. For example in this work, histogram of oriented gradient (HOG) is used as feature extraction and SVM and classical NN as classifier to classify the visual field defects. Through deep learning, on the other hand, the network receives both the boundary box coordinates and all the corresponding labels of the object, and network learns to locate and classify itself [33].

Besides that, in this work, there are 2 types of datasets: separated left and right eyes and both eyes. Both of these datasets are trained together to improve the performance of visual field defect classification. The separated left and right eyes dataset are obtained from data augmentation to increase the number of datasets.

The number of separated left and right datasets is double the size of both eyes dataset so it will be training frequently in the training process. It will be easy to predict compare to both eyes datasets. Besides that, less area of defect in separated eyes makes it also one of the reasons makes it easy to recognize. Figure 6, shows the example of the separated left and right eye datasets and both eyes datasets.

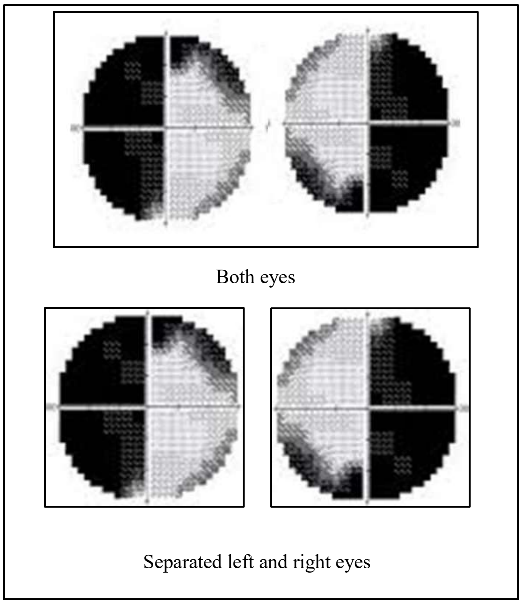


Figure 6. Comparison between 2 types of datasets

5. Conclusion

In this paper, a custom convolutional neural network model had been proposed, to detect six visual field defect patterns. Convolutional neural network, had been successfully employed in image classification is shown in this work that the classifications each type of visual field defect image are 91% for central scotoma, 98% for right/left/upper/lower quadratopia, 98% for right/left hemianopia, 100% for tunnel vision, 92% for superior/inferior field defect and 97% for normal. The recognition time for this work is greatly reduced by using Google Colab GPU.

It does not require feature extraction and segmentation and its performance is better compare to a traditional machine learning. The limitation of using CNN is that the training speed will be reduced and increase the risk of overfitting when the complexity of the model is increases. Overfitting problems can be avoided by using k-fold cross-validation and add some dropout layer in the model. There are many other extraction methods and combinations that need to be studied such as convert the visual images in to Voronoi image or combination of deep learning method for example combination of CNN and RNN.

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