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APPLICATION OF DEEP LEARNING TECHNIQUE FOR AUTOMATED HEALTHCARE DATA LABELING

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ABSTRACT

This paper on automated data labeling for health care using integrated deep learning technique was aimed at developing a software application system in medical image classification. To achieve this, data of health care images was collected from Nigerian hospitals considering four classes of eye conditions which are cataract, glaucoma, diabetes and normal eye. The data was extracted with the application of Mobile-Net version 2, which is a deep learning algorithm carefully designed with series of convolutional filters with the ability to extract spatial and intricate image information for training purposes. The extracted feature vectors were formed as a data matrix using global average pooling layer and then feed to a clustered based neural network algorithm and trained with back-propagation to generate a model for health care classification and labeling. During the training of the neurons, Self-Organized Map (SOM) were formulated through the adjustment of the neurons and clustering similar data points in a grid map, until convergence. The model generated was deployed as a software application for diagnosis of eye diseases using Tensorflow and MATLAB programming language and then evaluated using real-life data of health care images.

Keywords: Data Labeling; Deep Learning; Mobile-Net; Clustered Based Neural Network; Self-Organized Map (SOM)

1. INTRODUCTION

Automated Image data labeling also known as automatic image annotation is a method of assigning descriptive tags of labels to images without the intervention of human with a computer software program. The process of automatic image labeling involves the use of artificial intelligence algorithms on different stages like feature extraction, image recognition, label assignment, confidence scores and fine tuning. Automated image labeling has practical applications such as content-based image retrieval, e-commerce, medical imaging, social media and photo sharing, security surveillance and natural language processing.

Artificial Intelligence (A.I) is the ability of a computer or electronic device to perform tasks mimicking human intelligence autonomously. A.I in healthcare involves the use of machine learning algorithms (deep learning, natural language processing, and image processing techniques) for analysis of vast amount of health care data for making predictions, recognition of patterns and assisting healthcare professional in the decision making. The application of A.I in healthcare is an innovative way of applying the intelligent technology for improving patient care, streamlining administrative tasks and enhancement of medical research. Specifically deep learning model, has evolved as the major type of A.I specialized for medical image classification and labeling. One major application of image labeling in healthcare is the diagnosis of eye diseases. The eye is a complex and very sensitive part of the body. This part of the body requires frequent care and management as there are many factors such as diseases, dirty, which can result to mis-functioning of the system. Various components within your eye collaborate to focus on objects and transmit visual data to your brain (Galloway et al., 2006). Numerous factors, such as certain conditions and injuries, can alter your eyesight, with some potentially resulting in permanent vision impairment (Cleveland Clinic, 2021).

There have been previous attempts by researchers to address the issues of eye problem using various deep learning techniques such as (Ilyasova and Demin, 2022; Tong et al., 2020; Lu et al., 2018; Han, 2022), through automated data labeling approach. Additionally, numerous conditions have the potential to impact the functioning of your eyes, including common vision issues like myopia (nearsightedness), astigmatism, and eye traumas. Furthermore, several diseases and disorders that may not primarily relate to the eyes can have repercussions on eye health, encompassing autoimmune ailments, diabetes, and hypertension (Cleveland Clinic, 2021); however, despite the success achieved, issues such as variability in results, unreliability, etc. (Peter, 2021).

In the past, machine and deep learning techniques have been applied for automated data labeling in health care, however issues such as inconsistencies in labeling, resource intensive requirement, limited availability of expert annotator and delay in the existing system presents the need for an automated data labeling system. This paper therefore proposed an integrated deep learning for automated data labeling in healthcare.

2. RESEARCH METHODOLOGY

The methodology used for the research is the Extreme Programming (XP) approach. The approach used to achieve the first objective which is to develop an integrated deep learning model for health care labeling using health care data, Mobile-Net-Version-2 as the pre-trained model for feature extraction and then a clustered base neural network for classification of the health care image label. To improve the efficiency and scalability of the model, the health care classification model generated after training the neural network was integrated as a mobile application software for the health care classification and labeling. To enhance the labeling consistencies of the model, rigorous test was performance with diverse data types and results were discussed and also validated.

2.1 Data collection

The dataset of medical images used for this work was collected from three Nigerian hospitals as the primary data source. The hospitals are University of Nigeria Teaching Hospital (UNTH), Enugu state, who provided 1098 files of diabetes retinopathy, Niger foundation hospital Enugu, who provided 1007 data of Glaucoma and 1038 data of Cataract, while Nnamdi Azikiwe University teaching hospital provided 1078 data of normal eye. Overall, the sample size of data collection is 4217 health care images, which were annotated and labeled using Python labeler and then store for feature extraction as the training dataset. For secondary dataset, samples of self-volunteered eye images were used test the model.

2.2 Feature Extraction with deep learning model

The feature extraction process was applied in this research for the extraction of image features collected for training of the machine learning algorithm and generation of the model for health care classification. This was achieved with Mobile-Net which is a deep learning algorithm.

2.3 Mobile-Net for feature extraction

Mobile-Net is made of bottleneck, depth-wise separable convolution, and pointwise convolution. The Depth-wise Separable Convolution (DSConv) is an essential part of the architecture of Mobile-Net. Depth-wise convolution and pointwise convolution are the two successive convolutional layers used in this method. Each input channel is convolved independently using a different set of filters in depth-wise convolution, producing a collection of intermediate feature maps. This phase applies a single convolutional filter per input channel, which reduces computational cost. Nonlinear interactions between features are made possible by applying pointwise convolution after depth-wise convolution to merge the intermediate feature maps across channels. Because of its lightweight design, which strikes a fair compromise between accuracy and model size, it works well in embedded and mobile applications with constrained processing resources.

2.4 A Clustered-Based Neural Network (CBNN) for classification

The specific clustered-based neural network applied in this study is the Self-Organizing Map (SOM), which utilizes a competitive learning algorithm (back-propagation) to organize neurons into a low-dimensional grid. In SOM, each neuron is associated with a weight vector representing a point in the input space of the health care data, and during training, neurons compete to become activated based on their similarity to the input data. Neurons that are close to

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each other in the grid tend to respond to similar input patterns, resulting in a topological mapping of the input space. This property makes SOMs useful for exploratory data analysis and understanding the underlying structure of complex datasets, as well as for tasks such as image recognition, where preserving the spatial relationships between features is important.

3 TRAINING AND EVALUATION OF THE HEALTHCARE IMAGE LABELING MODEL

To train the CBNN model, the Gradient Descent (GD) back-propagation algorithm (Tian et al., 2023) was utilized. During the training of the model, the data was imported into the model using and then automatically split into training, test and validation. Additionally, GD was utilized to adjust the CBNN hyper-parameters such as weights, bias, momentum and learning rate, while monitoring the gradient loss. During the training process, regularization algorithm such as drop-out (Thomas, 2014; Ivana et al., 2020) was applied to address the issues of over-fitting of neurons. This process randomly selects neurons with large weight and then dropout to generalize the model. During the training process, parameters such as loss, accuracy were utilized to evaluate the performance of the model, considering the test and validation sets. During this process, then the performance is poor, the hyper-parameters were adjusted and the training and evaluation process continued iteratively. At the end of the training process, when the gradient loss is tolerable, the model for the healthcare labeling is generated.

3.1 Mathematical modelling of the feature extraction techniques with Mobile-Net-V2

The modelling of Mobile-Net primarily consists of the depth-wise separable convolutional layers which is mathematically defined as equation 1;

$$Y = {}_{i=1}^{C} w_i * X_i \qquad 1$$

Where Y is the output of the feature map, C is the number of channels, X_i is the input to the channel and w_i is the depth-wise filter applied to each of the input channel. The model of the point wise convolution is presented as;

$$z = {}_{j=1}^{M} v_i * Y_j \qquad 2$$

Where Z is the output of the point wise convolution, M is the output channel, Y_i is the depth-wise convolution and v_j is the point-wise filter at the output channel. A combination of equation 1 and 2 presents the bottleneck of the Mobile-Net in equation 3;

$$Y = {}_{j=1}^{M} {}_{i=1}^{C} v_i * w_i * X_i \qquad 3$$

This equation 4.3 represented the process of depth-wise separable convolution, where each input channel is convolved with its own depth-wise filter w_i, followed by a point-wise convolution to combine the resulting feature maps. This process reduces computational complexity while preserving expressive power, making it suitable for efficient image feature extraction which was the target of its application in this research. The Figure 2 presents the block diagram of the Mobile-Net extractor.

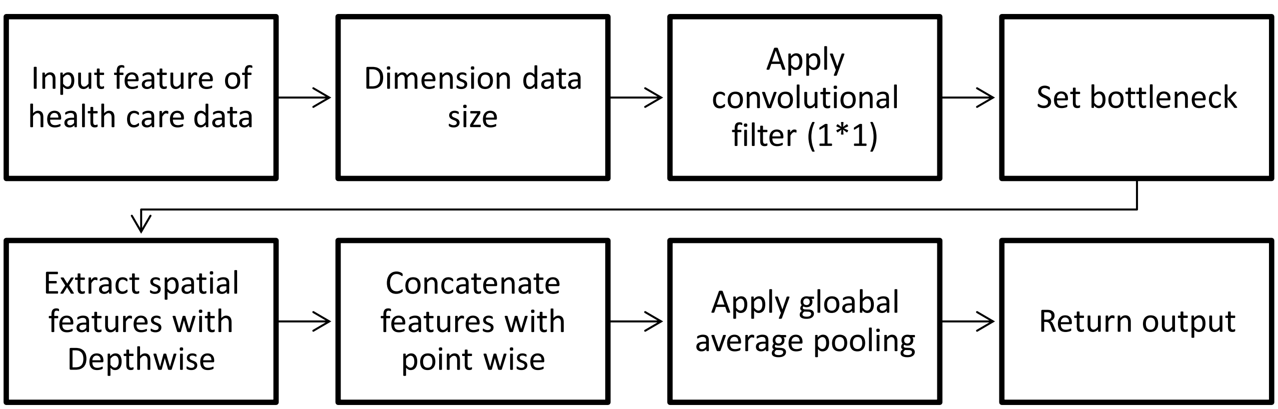

Figure 2: Block diagram of Mobile.Net extractor

In the Figure 2, the input image from the dataset are first automatically dimensioned by the MobileNet input layer in the size of 160*160*3 for the height, weight and colour channel, then the convolutional filter of 1*1 is applied by bottleneck which utilizes depth-wise convolution to extract the spatial information of the image vector and then combine them with the point wise convolution before applying the average global pooling techniques to represent the extracted vectors in a data matrix. The architecture of the Mobile-Net configuration is presented in Table 1.

Table 1: Mobile-Net-V2 Architecture Table

Layer	Input Size	Output Size	Filter Size	Stride	Activation
Input Image	Height x Width x Channels	Height x Width x Channels	-	-	-
Convolution	H x W x C_in	H/2 x W/2 x 32	3x3	2	ReLU6
Bottleneck1	H/2 x W/2 x 32	H/2 x W/2 x 32	1x1	1	ReLU6
Bottleneck2	H/2 x W/2 x 32	H/4 x W/4 x 16	1x1	1	ReLU6
Depthwise	H/4 x W/4 x 16	H/4 x W/4 x 16	3x3	1	ReLU6
Bottleneck3	H/4 x W/4 x 16	H/4 x W/4 x 24	1x1	1	ReLU6
Depthwise	H/4 x W/4 x 24	H/4 x W/4 x 24	3x3	2	ReLU6
...	...	...	...	...	...
Bottleneck9	H/16 x W/16 x 96	H/16 x W/16 x 160	1x1	1	ReLU6
Depthwise	H/16 x W/16 x 160	H/16 x W/16 x 160	3x3	2	ReLU6
...	...	...	...	...	...
Bottleneck10	H/32 x W/32 x 160	H/64 x W/64 x 320	1x1	1	ReLU6
Convolution	H/64 x W/64 x 320	H/64 x W/64 x 1280	1x1	1	ReLU6
Global Avg	H/64 x W/64 x 1280	1x1x1280	-	-	-

3.2 Mathematical modelling of the Clustered Based Neural Network

The mathematical modelling of a clustered based neural network began with an input layer x defined as Equation 4 and the cluster layer defined in Equation 5 (Naskath, et al., 2022);

$$X = [x_1, x_2, \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots ., x_n]^T \quad 4$$

$$F_{c(x)} = \text{arg min} \, {}_{i=1}^{m} |x - c_i| \quad 5$$

Where c_i is the centroid of $i - th$ cluster, T is the transpose function, and m is the number of clustered, while the cluster assignment function is presented as $F_{c(x)}$ with x the nearest centriod. This centriod represents the features of the image data extracted with Mobile-Net, and then feed to the hidden layers of the neural network which is presented as Equation 6;

$$h_j = \partial_{i=1}^{m} w_{ji}^{(1)} . F_c(x)_i \; + b_j^{(1)} \quad 6$$

Where $w_{ji}^{(1)}$ is the weight connecting the $i - th$ cluster to the $j - th$ neuron, $b_j^{(1)}$ is the bias of the $j - th$neuron, ∂ is the activation function, and j is the neuron. For subsequent nth layer of the hidden neuron, the Equation 7 presented it as;

$$h_j = \partial_{i=1}^{m} w_{ji}^{(n)} . F_c(x)_i \; + b_j^{(n)} \quad 7$$

While the output layer is presented as equation 8;

$$O_l = \partial_{j=1}^{p} w_{jk}^{(n)} . h_j \; + \; b_k^{(n)} \quad 8$$

Where $w_{jk}^{(n)}$ is weight, $b_k^{(n)}$ is the bias of $k - th$ neurons. The Figure 3 presented the architectural model of the clustered based neural network model and behaviour of neurons during training process with the imported feature vector and optimization back-propagation technique.

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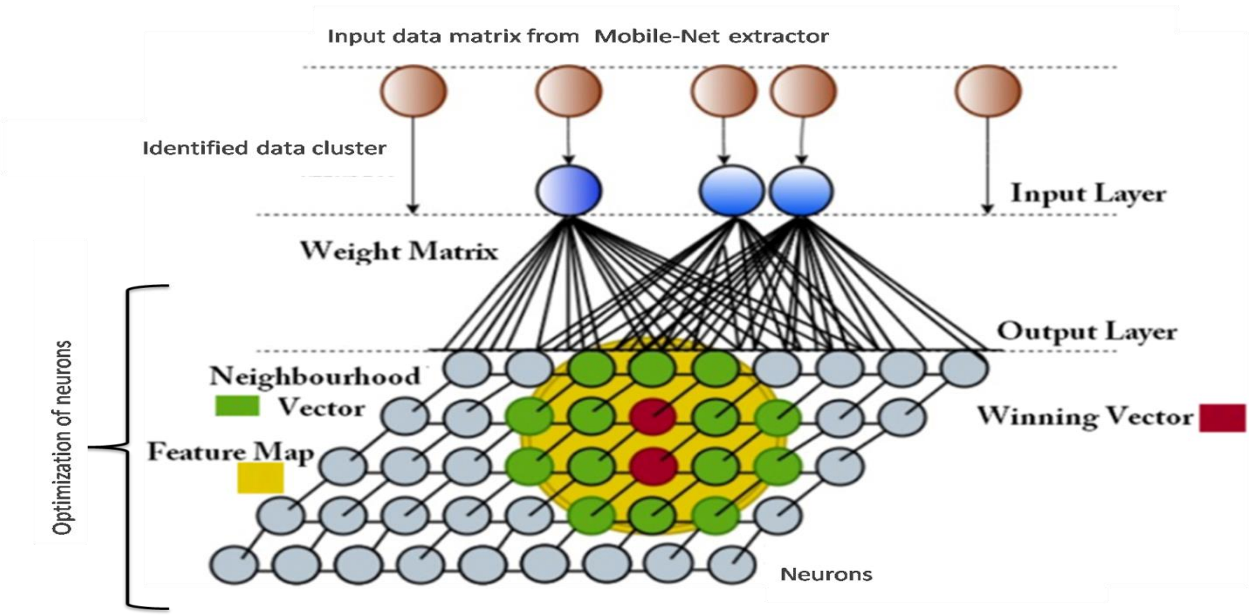

Figure 3: Cluster based neural network architecture

The Figure 3 showcased the cluster based neural network architecture during the training process with the imported data extracted by Mobile-Net. First the data matrix extracted from the Mobile-Net are feed to the network as clustered through the input layer. The neurons are assigned to the data based on their weight matrix and then during training, the neighbouring vectors are mapped out based on their distance, while the closest distance neighbours are identified as the wining vector which is the matched image class during classification. During the training of the neurons with data of health care collected, loss function is applied to evaluate the performance of the model, monitoring error during training and ensuring that the best version of the model with minimized error was achieved.

$$L = \frac{1}{N}{}_{i=1}^{N}(O_i - y_i)^2 \qquad 9$$

During the optimization process, the weight and bias of the neurons are optimized to minimize loss function. This process utilized gradient descent to update the direction of the minimized loss.

Output layer

The output layer of the model utilized accuracy of the classification and then the label to identify the health care data status and also the probability of correct classification rate. The accuracy measured the trustworthiness of the classification output and used to repot the model confidence of the classification output. The step sequence block diagram of the clustered based neural network is presented as Figure 4;

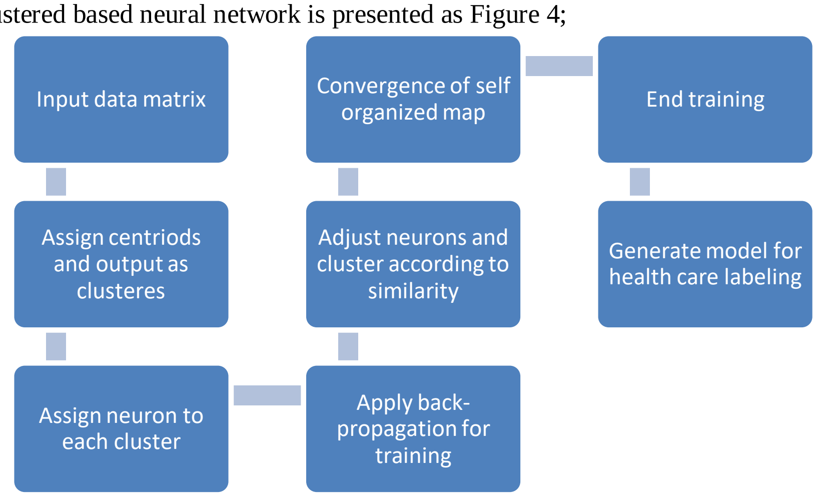

Figure 4: Block diagram of the Clustered based neural network

3.3 Flowchart of the Intelligent Model for Health Care Labeling

The section presented the system flow chart, starting with the flow chart of the feature extraction process, that of the classification process and then the complete system flow chart for health care labeling. The Figure 5 presented the result of the feature extraction process with Mobile-Net. First the data of health care is collected and load to Mobile-Net which utilized the depth-wise convolution in Equation 1 to extract the intricate spatial pixel information of the image and then the point-wise convolution in Equation 2 that utilized 1*1 convolutional filter to combine and transform the output of the depth-wise convolution. The combined features in Equation 3 are down-sampled with rectified linear unit activation function and then pooled with the average pooling layer to generate the feature vectors needed to train the clustered based neural network in the Figure 6;

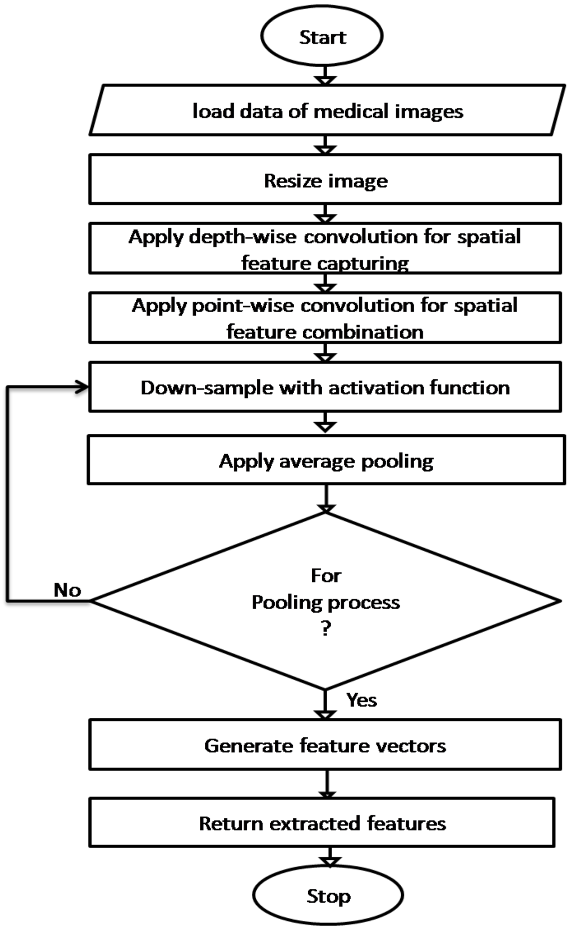

Figure 5: Flow chart of the Mobile-Net

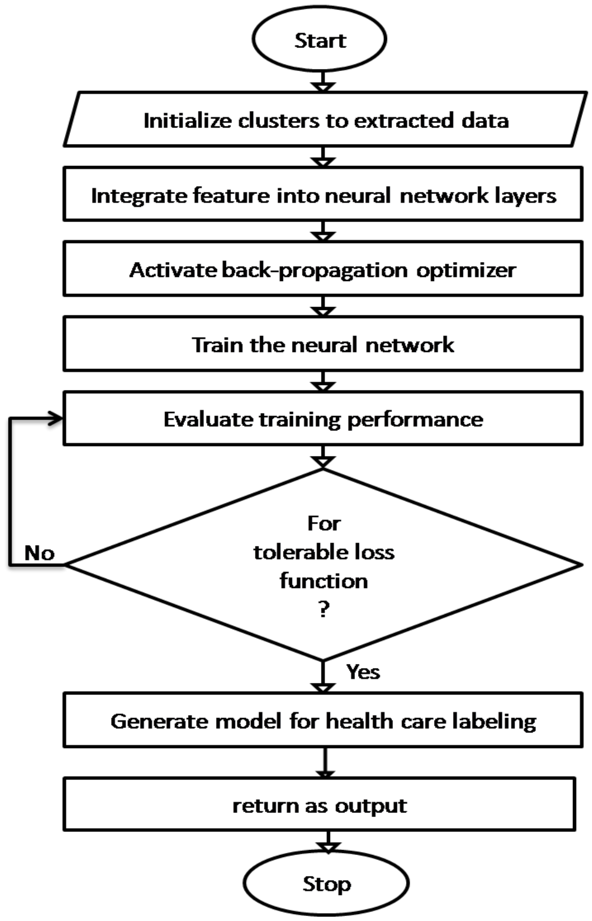

Figure 6: Clustered based neural network flow chart

The Figure 6 presented the flow chart of the clustered based neural network. First the data in Equation 4 extracted from the Mobile-Net is loaded into the network, which then assign clusters the each of the feature vectors using Equation 5. These clusters are feed to the hidden layers of neural network in Equation 7 and then apply back propagation optimizer to adjust the hyper-parameters of the neurons while monitoring with loss function in Equation 9 to generate the model for the health care labeling and classification

4 SYSTEM IMPLEMENTATION

We used TensorFlow and MATLAB together in our system implementation to provide a strong solution for healthcare picture classification, with an emphasis on eye illness diagnosis. The clustered-based neural network was trained with the help of MATLAB, which proved to be a useful tool in helping us categorize various eye disorders and arrange neurons into meaningful clusters. We were able to adjust the network's parameters and maximize its performance to produce precise and trustworthy results thanks to MATLAB's large library of functions and toolboxes designed specifically for machine learning and neural networks.

Furthermore, TensorFlow was essential to our system's feature extraction process. In particular, we used TensorFlow pre-trained convolutional neural network architecture to extract features from Mobile-Net using embedded and mobile vision applications. We successfully extracted high-level features from the input photographs by utilizing Mobile-Net's effective design. This allowed us to identify significant patterns and traits that are pertinent to the diagnosis of eye illnesses. Our entire classification model benefited greatly from these extracted features, which improved its capacity to distinguish between various illness stages and classify photos appropriately.

We blended the advantages of both platforms to provide a complete solution for healthcare image labeling and classification by integrating MATLAB and TensorFlow. We were able to develop a complex model for precisely diagnosing eye illnesses based on medical photos by utilizing TensorFlow's effectiveness in feature extraction with Mobile-Net and MATLAB's training capabilities for clustered-based neural networks. This synergistic approach not only enabled us to achieve superior performance in disease classification but also laid the foundation for future enhancements and scalability of our healthcare imaging system

5 RESULTS AND DISCUSSION

In the performance evaluation, the result of the models feature extraction, training was evaluated and reported in this section. After testing software, the results are compared between the predicted and real, and any differences are reported as faults. The test is declared successful if the actual result matches the predicted outcome; if not, it is declared unsuccessful. Determining the accuracy and functioning of the program under test requires comparing the actual and predicted results.

5.1 Result of Mobile.Net-V2 Feature extraction

The result of the Mobile-Net feature extraction process was presented in the table 4.3 showing the series of features extracted from the original input health care images collected at 160*160*3 dimension and then output as earlier defined in the Mobile-Net architectural model in Table 1. In the Table 2, the corresponding results of each features extracted and concatenated at the bottleneck and every step of the depth-wise convolution are reported. In the table the bottle neck which uses 1*1 convolution are applied to reduce the number of colour channels in the image, while the depth-wise convolution used filter to extract spatial image features which are feed to the next bottle next for similar processing, which facilitates reduction in the image size due to dimensionality reduction, while maintaining quality of service, and the activation function is then applied for normalization.

Table 2: Result of feature extraction with Mobile-V2

Layer	Input Size	Output Size	Filter Size	Stride	Activation
Input Image	160x160x3	160x160x3	-	-	-
Convolution	160x160x3	80x80x32	3x3	2	ReLU6
Bottleneck1	80x80x32	80x80x32	1x1	1	ReLU6
Bottleneck2	80x80x32	40x40x16	1x1	1	ReLU6
Depthwise	40x40x16	40x40x16	3x3	1	ReLU6
Bottleneck3	40x40x16	40x40x24	1x1	1	ReLU6
Depthwise	40x40x24	40x40x24	3x3	2	ReLU6
...	...	...	...	...	...
Bottleneck9	10x10x96	10x10x160	1x1	1	ReLU6
Depthwise	10x10x160	10x10x160	3x3	2	ReLU6
...	...	...	...	...	...
Bottleneck10	3x3x160	3x3x320	1x1	1	ReLU6
Convolution	3x3x320	3x3x1280	1x1	1	ReLU6

Global Avg	3x3x1280	1x1x1280	-	-	-

Table 2 presented the results of the Mobile-Net feature extraction process, in-line with the model of Table 2 presented the architecture of the Mobile-Net, Meanwhile Table 3, showcases a complete feature representation of the health care data extracted was reported showing the extracted spatial information from the first bottleneck till the lacks and then the average global pooling which pools the final feature vector to train the clustered based neural network. The ReLU6 is used to denote that the ReLU activation function with a maximum threshold of 6 and applied to the output of each layer. This helps keep the activations within a bounded range of 0 to 6, which can be beneficial or dimensionality reduction, while maintaining quality of data extracted.

Table 3: Complete result of the Mobile-Net-V2 feature extraction process

Layer	Input Size	Output Size	Filter Size	Stride	Activation
Convolution	160x160x3	80x80x32	3x3	2	ReLU6
Bottleneck1	80x80x32	80x80x32	1x1	1	ReLU6
Bottleneck2	80x80x32	40x40x16	1x1	1	ReLU6
Depthwise	40x40x16	40x40x16	3x3	1	ReLU6
Bottleneck3	40x40x16	40x40x24	1x1	1	ReLU6
Depthwise	40x40x24	40x40x24	3x3	2	ReLU6
Bottleneck4	40x40x24	20x20x32	1x1	1	ReLU6
Depthwise	20x20x32	20x20x32	3x3	1	ReLU6
Bottleneck5	20x20x32	20x20x32	1x1	1	ReLU6
Depthwise	20x20x32	20x20x32	3x3	1	ReLU6
Bottleneck6	20x20x32	10x10x64	1x1	1	ReLU6
Depthwise	10x10x64	10x10x64	3x3	2	ReLU6
Bottleneck7	10x10x64	10x10x96	1x1	1	ReLU6
Depthwise	10x10x96	10x10x96	3x3	1	ReLU6
Bottleneck8	10x10x96	10x10x160	1x1	1	ReLU6
Depthwise	10x10x160	10x10x160	3x3	2	ReLU6
Bottleneck9	10x10x160	10x10x160	1x1	1	ReLU6
Depthwise	10x10x160	10x10x160	3x3	2	ReLU6
Bottleneck10	10x10x160	3x3x320	1x1	1	ReLU6
Convolution	3x3x320	3x3x1280	1x1	1	ReLU6
Global Avg	3x3x1280	1x1x1280	-	-	-

From Table 3, the feature extracted by the Mobile-Net are presented and at the each of the convolution process, the global average pooling which computes the average pixel value of every convolutional stride and reported a final feature vector output size of 1*1*1280, which mean that after he feature extraction process, 1280 features were selected from the image, which represents the best part for training the model for health care labeling.

5.2 Result of the clustered based neural network for health care labeling

In the evaluation of the clustered based neural network training performance, the SOM learn the high dimensional features vectors to lower dimensional grid neurons during training considering the data structure. The SOM weight distance result is presented in the heat map of Figure 7.

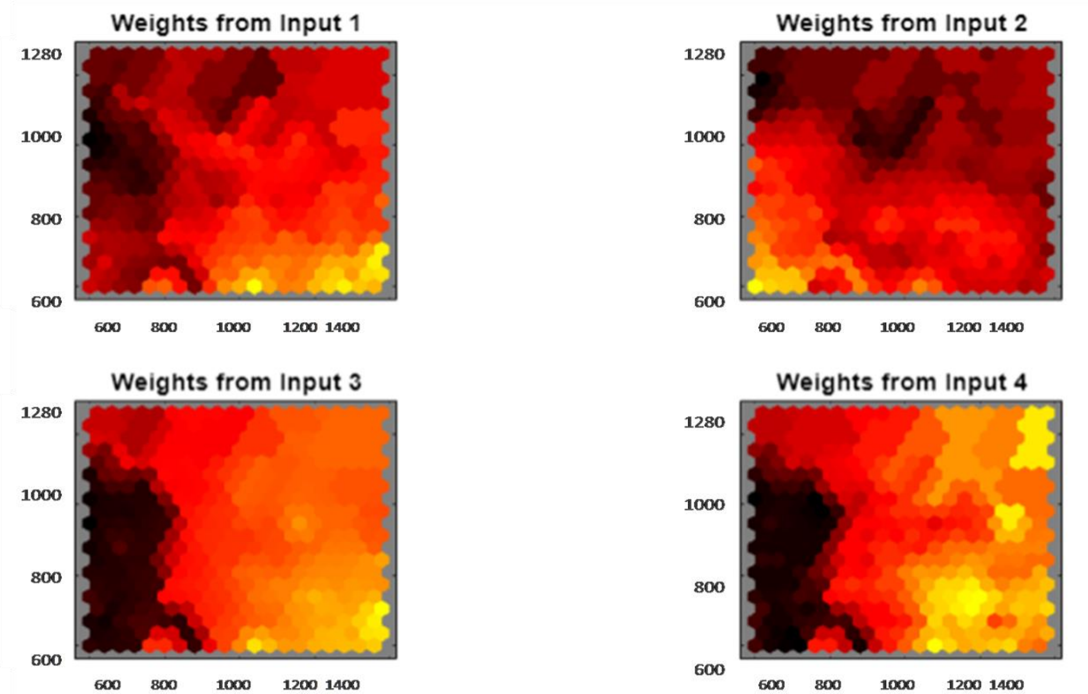

Figure 7: SOM results from the input features

The Figure 7 presented the SOM of the input data from Mobile-Net. The data were automatically identified as Equation 4 and then assign clustered using Equation 5 as shown in the results. From the map, it was observed that similar features are clustered in the same region of the grid map, considering their neighboring distance through the application of equi-distance principle as shown in the Figure 8.

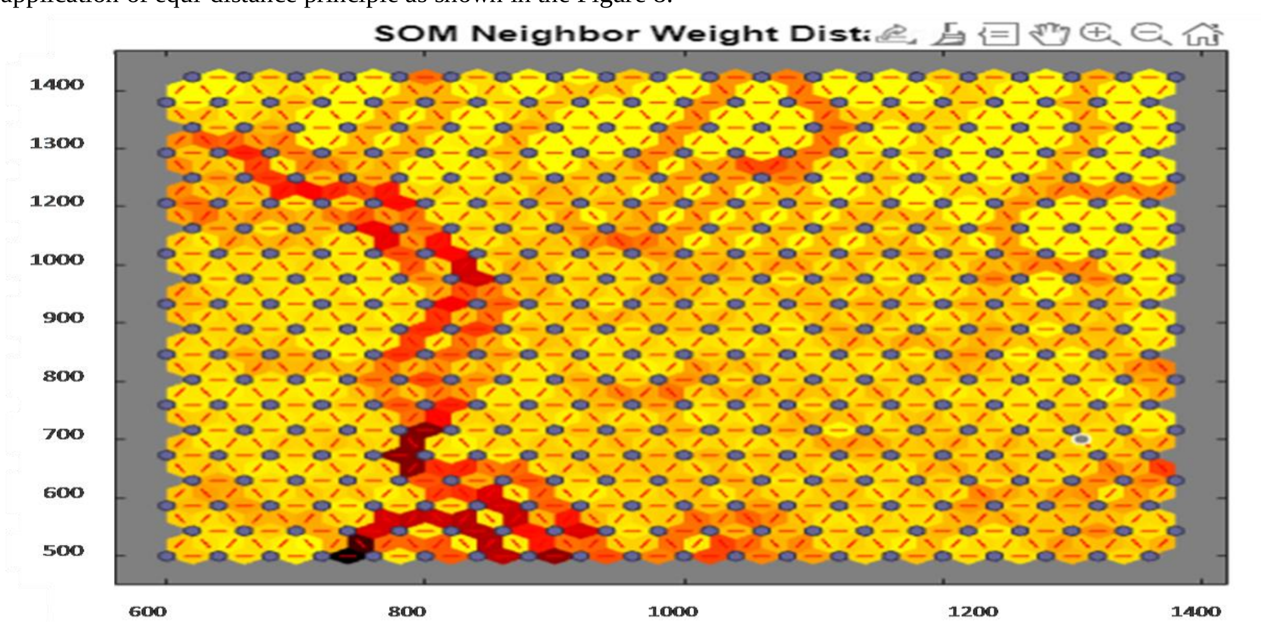

Figure 8: SOM result of the weight distance computation to determine grid map

The Figure 8 presented the result of the SOM which computes the sum of weight distance of the neurons during the training process. As the neurons are trained, each of the weight SOM gird has a weight vector which represents the centriod of the clusters. The distance between each of the nodes is used to select similar nodes that are clustered together. The Figure 9 presented the SOM weight position within the grid. The essence of this result is to analyze how the neurons are distributed within the hidden layer model of Equation 7 during the training process, applying the back-propagation optimizer. During this process, while the neurons are adjusted automatically, the ones which are similar are clustered together meaning that they represent similar input which can be normal, Glaucoma, diabetes or cataract eye images set, while SOM for the neuron Hit frequency is in figure 10.

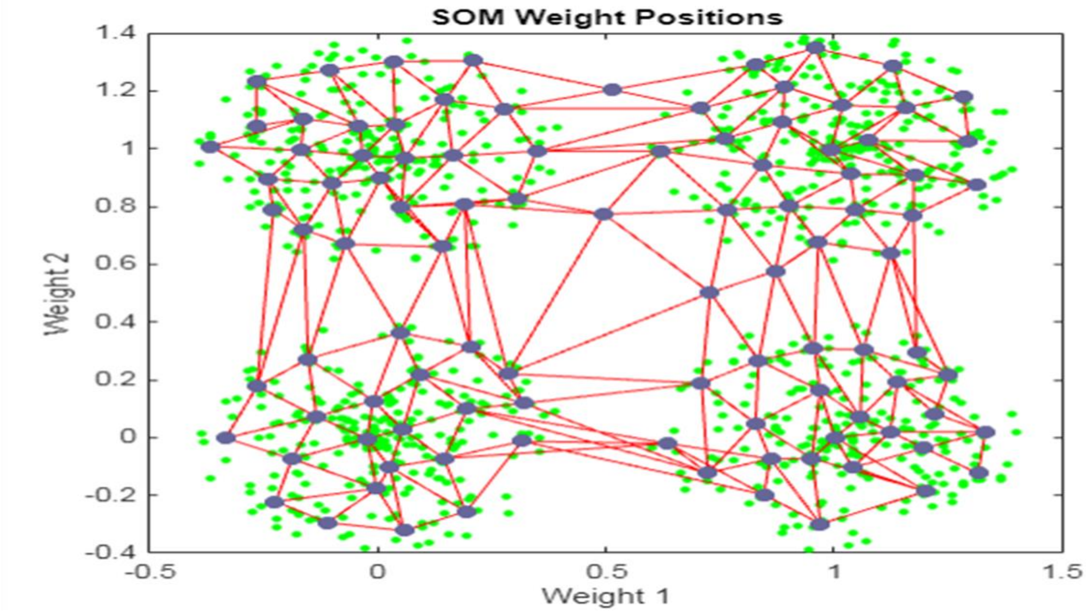

Figure 9: SOM weight position during training

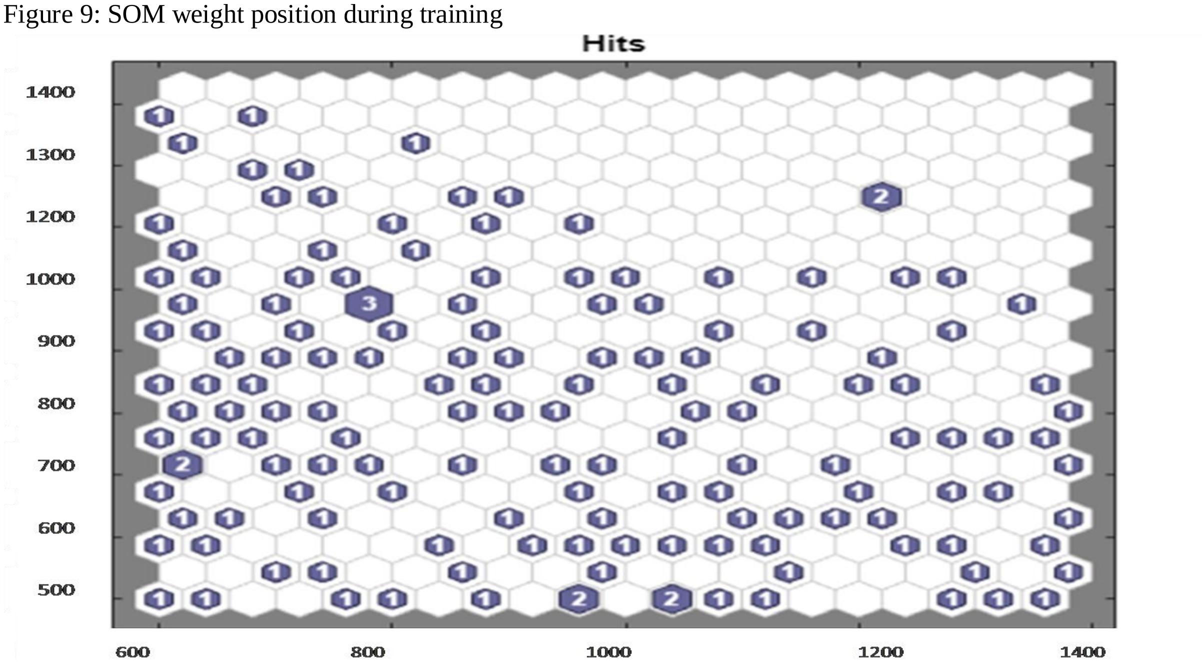

Figure 10: SOM for the neuron Hit frequency

The Figure 9 presents the SOM for the position of neurons during the training process. In the results, the neurons are clustered into four major part of the gird, and this is performed based on their similarity in data input and their current weight value. This ensures that neurons which are closer in the input data within the feature space are clustered together in similar positions. During the training process, the frequency at which the best matching neurons are selected is called the hits and the result is presented in the Figure 10. This his drives the adaptivity of the SOM grid during the training of the neural network and the neurons which receives hits are adjusted automatically to better represent the input data which results to the self-organization of the maps and the emergence of a certain pattern representation of the clusters. The Figure 10 presents the Hits in SOM and are represented with number between 1, 2 and 3 which respectively corresponds to the grid neurons which best match the input data. This hit represents how often each of the neurons in the SOM grid is selected as the best matching unit during the optimization training process and the neurons which are frequently selected is considered the most representative of the input image data which mean the neuron which represents the best part of the medical input image.

6 CONCLUSION

In this study, we embarked on a journey to develop a deep learning model tailored specifically for automated data labeling in healthcare, with a primary focus on facilitating personalized diagnosis of healthcare challenges, particularly eye diseases. By addressing the complexities health care data, our research aimed to revolutionize the way healthcare professionals diagnose and treat patients, ultimately leading to improved patient outcomes and enhanced quality of care. The cornerstone of our research endeavor was the development of an integrated deep learning framework that seamlessly integrates advanced machine learning algorithms such as clustered based neural network and deep learning such as MobileNet with medical imaging data. Through design and implementation, the study aimed to create a robust framework capable of efficiently and accurately labeling medical images, thereby enabling rapid and precise diagnosis of eye diseases. By leveraging state-of-the-art deep learning techniques, we endeavoured to bridge the gap between traditional diagnostic methods and cutting-edge technological innovations, paving the way for a new era in healthcare diagnostics.

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