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INTELLIGENT MEDICAL IMAGE DATA LABELLING HEALTHCARE AUTOMATION USING DEEP LEARNING TECHNIQUE

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Abstract

The goal of this paper was to create a software application system medical image classification through automated data labelling for healthcare utilising an integrated deep learning technique. The four categories of eye conditions such as cataract, glaucoma, diabetes, and normal eye were taken into consideration when gathering health care imaging data from Nigerian hospitals. The deployment of Mobile-Net-2, a deep learning technique with a number of convolutional filters that can extract complex and spatial visual information for training, was used to extract the data. In order to create a model for health care classification and labelling, the collected feature vectors were first converted into a data matrix using a global average pooling layer. They were then fed into a clustering neural network algorithm and trained using back-propagation. Self-Organised Maps (SOMs), were created throughout the neurone training process by adjusting the neurones and grouping related data points together in a grid map until they converged. Using Tensorflow and the MATLAB programming language, the model was implemented as a software program for diagnosing eye conditions. It was then assessed using actual medical imaging data. When accuracy was taken into account, the findings showed that the condition was 97.039% for normal eye data, 99.421% for diabetic retinopathy, 90.926% for glaucoma, and 98.431% for cataracts. To validate the results, comparative analysis with other algorithms was performed and the results showed that the new model with Mobile-Net and Clustered based neural network achieved the best results.

Keywords: Medical Image; Data Labelling; Deep Learning; Mobile-Net-2; Convolutional Filters; Clustering Neural Network; Back Propagation

1. INTRODUCTION

According to Bitto and Mahmud (2022), data labelling is part of the pre-processing stage when developing a machine learning (ML) model. It requires the identification of raw data (i.e., images, text files, videos), and then the addition of one or more labels to that data to specify its context for the models, allowing the machine learning model to make accurate predictions (Alzubaidi et al., 2020). Data labelling underpins different machine learning and deep learning use cases, including computer vision and Natural Language Processing (NLP).

According to the National Institute of Health, (2022), data labelling in healthcare plays a pivotal role in leveraging the power of machine learning and artificial intelligence to improve patient care, diagnosis, and treatment outcomes. The healthcare sector in a submission by Roy et al., (2019) generates vast amounts of diverse data, ranging from medical images and clinical notes to

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genomic sequences and continuous monitoring data (Son et al., 2018). These datasets serve as the foundation for developing predictive models, personalized medicine, and data-driven decision support systems (Peter, 2021). However, the raw data is often unstructured and requires meticulous annotation to enable algorithms to learn and make meaningful predictions (Tao et al., 2021).

In medical imaging, data labelling involves annotating images with detailed information about structures, abnormalities, or specific regions of interest (Boniolo et al., 2021). Radiologists and healthcare professionals contribute their expertise to ensure accurate labelling, facilitating the training of models for tasks such as tumor detection, organ segmentation, and disease classification (Veena, 2022). Additionally, Wang (2019) posited that clinical text data, extracted from electronic health records, undergoes labelling to identify and categorize patient information, diagnoses, and treatment plans. The challenges in healthcare data labelling include the need for specialized domain knowledge, ensuring patient privacy and compliance with regulations, and addressing potential inter-annotator variability to maintain the accuracy and reliability of labelled datasets (Mahmoudet al., 2021; Shen et al., 2015).

Deep learning techniques have revolutionized data labelling in healthcare by providing efficient and effective solutions for handling large and complex datasets. One notable approach is the use of convolutional neural networks (CNNs) for image annotation tasks. CNNs excel at learning hierarchical features from medical images, automating the process of identifying structures, abnormalities, or specific patterns within the data (Acharya et al., 2006). Transfer learning is another powerful technique, where pre-trained models on large datasets can be fine-tuned for specific medical imaging tasks, reducing the need for extensive labelled data. Natural Language Processing (NLP) models play a crucial role in automating text annotation in healthcare. Recurrent Neural Networks (RNNs) and Transformer models, such as BERT and GPT, are adept at understanding the contextual nuances of clinical notes and electronic health records (Fourcade and Khonsari, 2019). These models can extract relevant information, including patient demographics, diagnoses, and treatment details, with high accuracy. This not only accelerates the data labelling process but also enhances the overall efficiency of healthcare workflows. In the past, machine and deep learning techniques have been applied for automated data labelling in health care, however issues such as inconsistencies in labelling, resource intensive requirement, limited availability of expert annotator and delay in the existing system presents the need for an automated data labelling system. This research therefore proposed an integrated deep learning for automated data labelling in healthcare.

2.0 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 labelling 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 as stated in objective two, the health care classification model generated after training the neural network was integrated as a mobile application software for the health care classification and labelling. To enhance the labelling consistencies of the model, rigorous test was performance with diverse data types and results were discussed and also validated with comparism with other state o the art models. To address the skilled gap, the software was deployed as a user friendly and low cost application software or self diagnosis of medical disorders like eye disease.

2.1 Data Acquisition

Three hospitals in Nigeria served as the main source of the medical imaging collection used in this study. The hospitals are Niger Foundation Hospital Enugu, which provided 1007 glaucoma and 1038 cataract data, University of Nigeria Teaching Hospital (UNTH), Enugu State, which provided 1098 diabetes retinopathy files, and Nnamdi Azikiwe University Teaching Hospital, which provided 1078 normal eye data. 4217 health care photos make up the total sample size of the data collection. These pictures were labelled and annotated using a Python labeller, and the training dataset was then stored for feature extraction. The model was tested using samples of self-volunteered eye pictures for the secondary dataset.

2.2 Database Design and Structure

The eye disease dataset comprises high-resolution retinal images labelled with four classes: cataract, diabetes, glaucoma, and normal eye. Each image is annotated with the corresponding disease category, allowing for classification and labelling tasks. The dataset features a diverse range of patients across age (25 to 75), groups (man and woman) and demographics (Nigeria), ensuring robustness and generalizability of the model. The images vary in terms of image quality, lighting conditions, and severity of the disease, providing a comprehensive representation of real-world clinical scenarios. The Figure 1 presented the database class diagram, showing the four classes of the dataset which are the glaucoma, cataract, diabetes and normal eye.

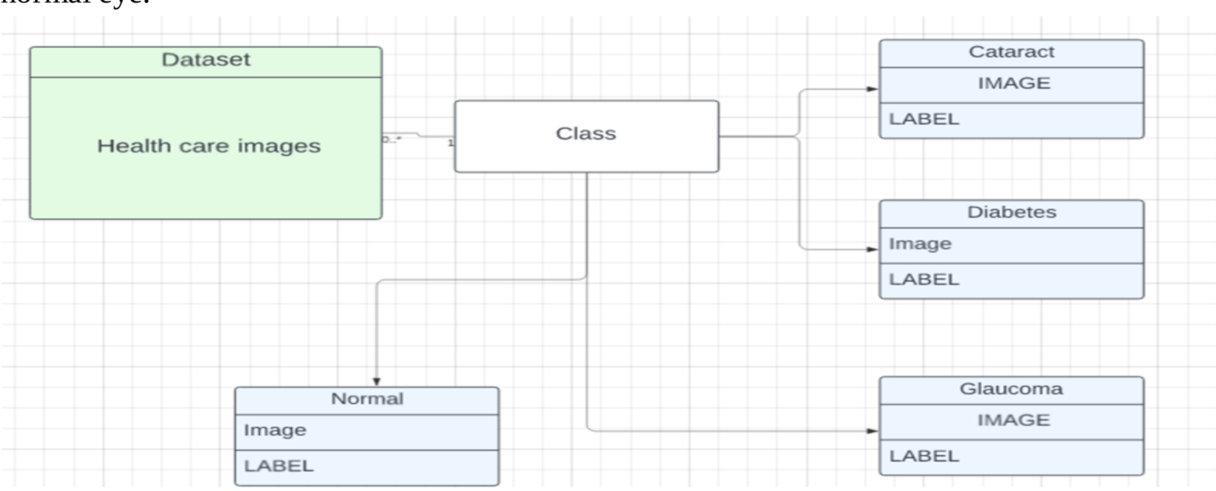


Figure 1: Class diagram of the data structure

2.3 Mobile-Net for feature extraction

Mobile-Net is made of bottleneck, depth-wise separable convolution, and point-wise convolution. The Depth-wise Separable Convolution (DSConv) is an essential part of the architecture of Mobile-Net. Depth-wise convolution and point-wise 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 point-wise 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.

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

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

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

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;

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

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;

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

This equation 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. 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 color channel, then the convolutional filter of 1*1 is applied by bottleneck which utilizes depthwise 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.

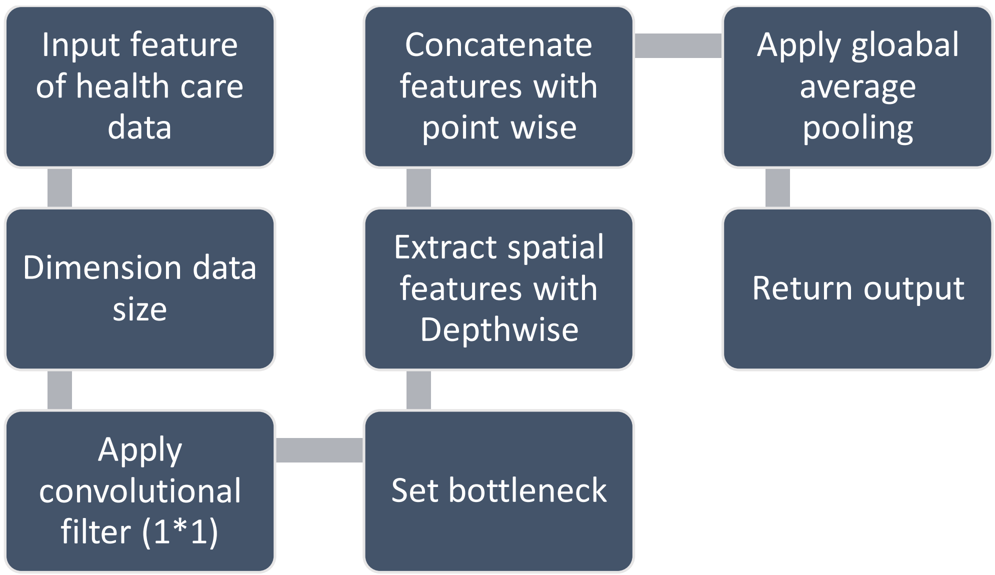


Figure 2: Block diagram of Mobile.Net extractor

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 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.

2.4.1 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);

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

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

Where c_i is the centriod 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;

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

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;

$$h_j = \partial \sum_{i=1}^{m} w_{ji}^{(n)} . F_c(x)_i + b_j^{(n)} \qquad 7$$

While the output layer is presented as;

$$O_l = \partial \sum_{j=1}^{p} w_{jk}^{(n)} . h_j + b_k^{(n)} \qquad 8$$

Where $w_{jk}^{(n)}$ is weight, $b_k^{(n)}$ is the bias of $k-th$ neurons. The figure 6 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. 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. 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.

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

2.4.2 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 report the model confidence of the classification output. The step sequence block diagram of the Clustered Based Neural Network (CBNN) is presented as figure 3, while the integrated system was presented in figure 4;

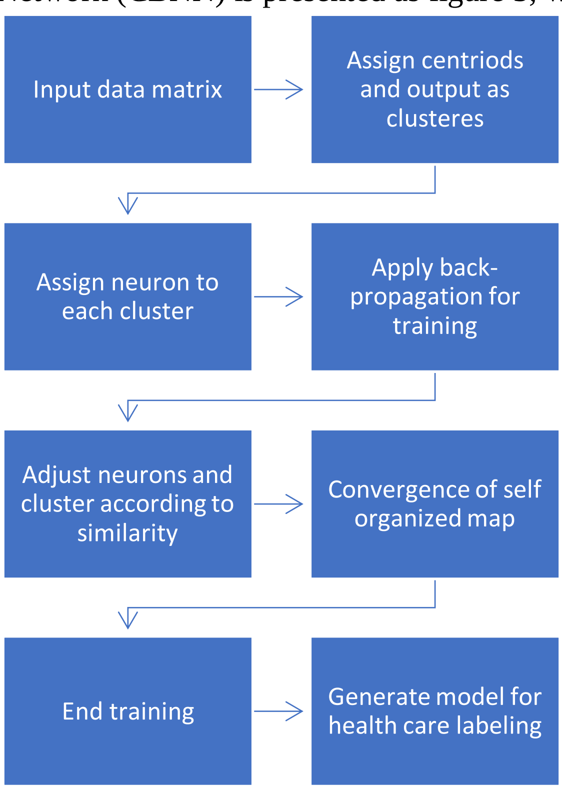


Figure 3: Block diagram of the CBNN

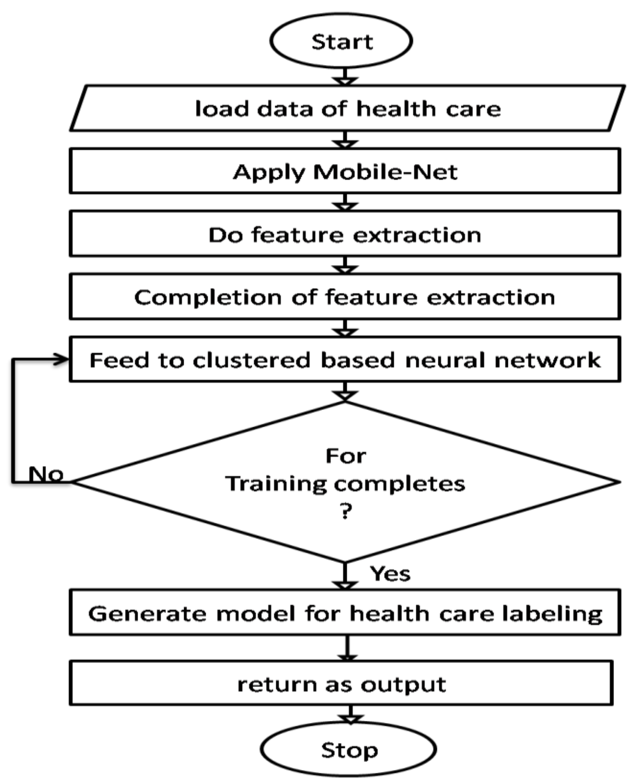


Figure 4: Flow chart of the integrated system

The Figure 4 begins with the collection of a diverse range of healthcare images specifically tailored towards eye diseases. These collected images serve as the fundamental input data for both training and evaluation of the system. To extract relevant features from the health care data collected, Mobile-Net which is a popular convolutional neural network algorithm was adapted, using the depth-wise separation which utilized filter of 1*1 convolution to extract spatial information and then concatenate with pointwise separation to form the bottleneck of the model. These bottleneck forms series of extracted feature vectors from the images in various sequence until the final layer where the average pooling layer extracts the final data. to train the data, a clustered based neural network was adapted and then trained with optimization back-propagation technique. The training ensure that similar neurons are clustered together hence representing the model's ability to classify the medical images extracted in clustered of the four datasets. Once the training is completed, the model for health care labelling is generated as shown in the high-level model of Figure 5.

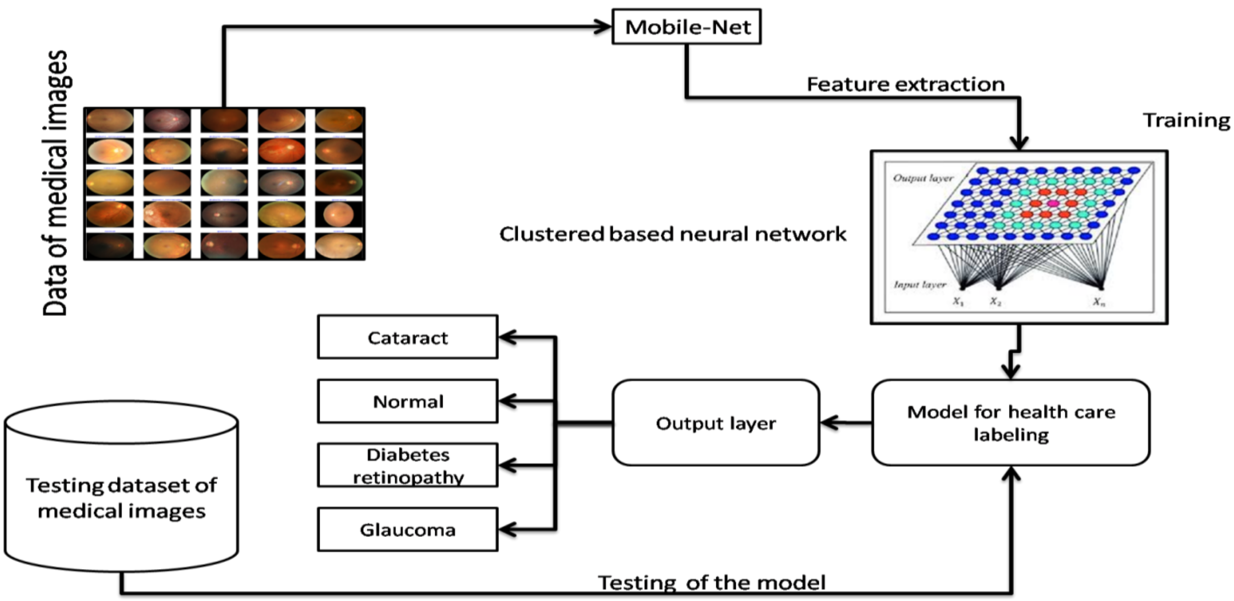


Figure 5: High level model of the proposed system

Figure 5 presents the high-level model of the proposed system, which showed how the training data was utilized for the development of the eyes disease classification model. The test data when imported to the model was then classified to detect the eye problem.

2.5 ALGORITHMS

The algorithms used in developing the new model for health image labelling are the Mobile-Net algorithm and the clustered based neural network algorithm.

Algorithm 1: Mobile-Net

1. *Resize input image, normalize pixel values, and convert to RGB.*
2. *Apply depth-wise convolution followed by point-wise convolution.*
3. *Sequentially stack multiple depth-wise separable convolution blocks.*
4. *Apply ReLU activation and optional down-sampling layers.*
5. *Replace fully connected layers with global average pooling.*

6. Generate feature vectors of health care images
7. End

Algorithm 2: Clustered Based Neural Network

1. *Randomly initialize cluster centers and assign each data point to the nearest cluster.*
2. *Update cluster centers by computing the mean of data points assigned to each cluster.*
3. *Integrate feature vectors into a neural network architecture as input layers.*
4. *Train the neural network using back-propagation from clustered data.*
5. *Optionally fine-tune cluster centers and neural network parameters*
6. *Pass input data through the neural network for classification.*
7. *Evaluate model performance*
8. *Deploy the trained model for health care labelling*
9. *End*

Algorithm 3: Deep learning model for health care labelling

1. *Start*
2. *Initialize feature extraction algorithm*
3. *Initialize classification model*
4. *Load data of health care*
5. *Extract feature vectors with depth-wise*
6. *Combine feature vectors with point-wise*
7. *Apply neural network for classification*
8. *Assign label to the classified output*
9. *Assign confidence accuracy score*
10. *End*

3.0 SYSTEM IMPLEMENTATION

The process of creating a healthcare picture labelling system involves several steps, including careful planning, precise design, complete implementation, stringent testing, and effective deployment. Clear goals and specifications are set at the planning stage, together with the target user base and resource allocation. This stage directs the project's scope, schedule, and resource management, laying the groundwork for later development phases.

As we proceed to the design stage, the components, user interfaces, and system architecture are outlined. Detailed methods and algorithms for image processing, feature extraction, and classification guarantee that the system will correctly identify photos of eye diseases. Additionally, a strong data pipeline is built to manage the import, pre-processing, and tagging of healthcare images, setting the foundation for effective data management throughout the system lifecycle. The development environment is configured, and the system components are constructed in accordance with the design specifications during implementation. While the neural network model is being created, TensorFlow is being used for feature extraction, and MATLAB is being used for training. The data pipeline is being implemented to ingest and pre-process healthcare photos. Automated labelling of photos related to eye diseases is made possible by the system's integration of the trained model, and user engagement and result visualization are enhanced by an intuitive interface. The system's functionality, accuracy, and performance are confirmed by rigorous testing and validation, guaranteeing that it is ready for implementation in actual healthcare settings.

4. RESULT AND DISCUSSIONS

This section presented the experimental validation of the model for health care classification and labelling. The results first presented the interface of the mobile application software as shown in the Figure 6. The mobile application result was presented which was developed utilizing the model generated for health care labelling using clustered based neural network and Mobile.Net. The software was tested with a health care data of diabetes retinopathy and the results was presented in the Figure 7.

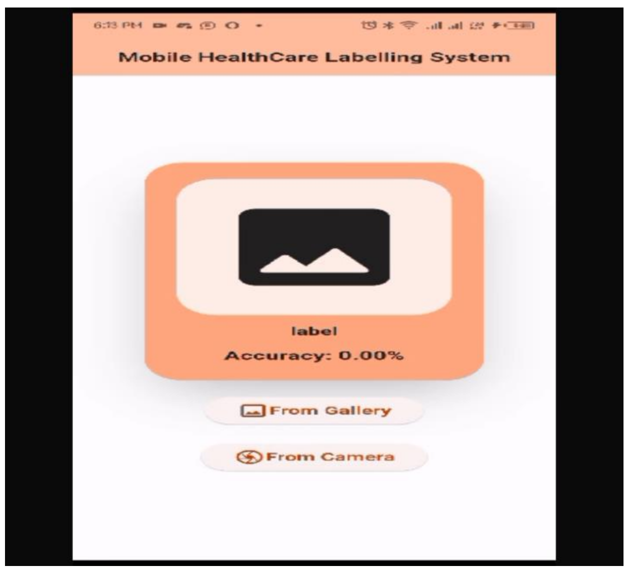
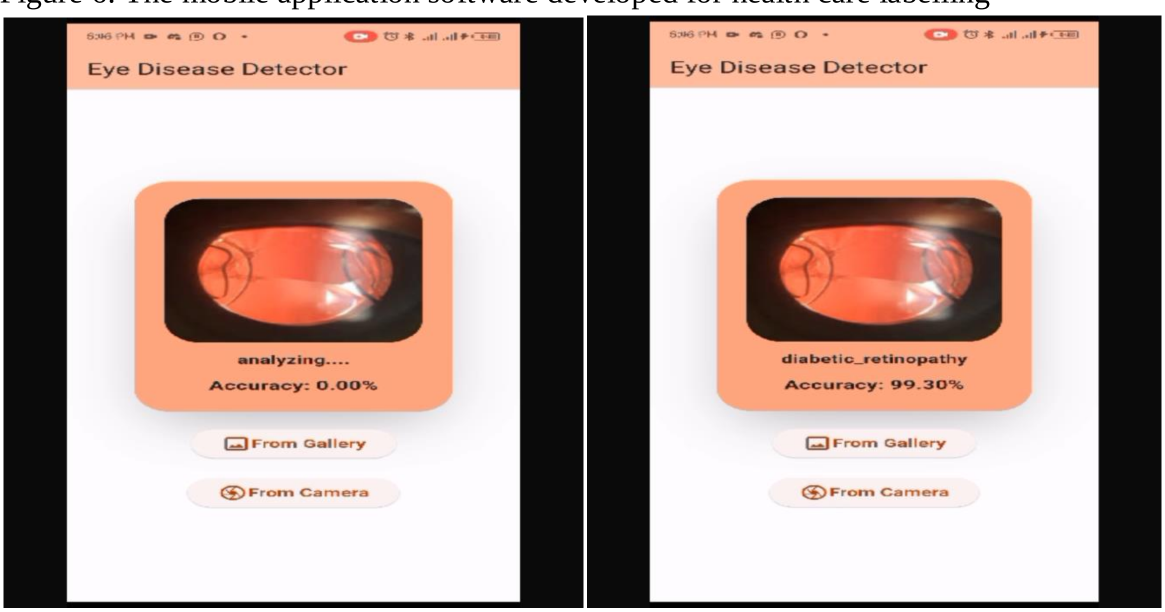


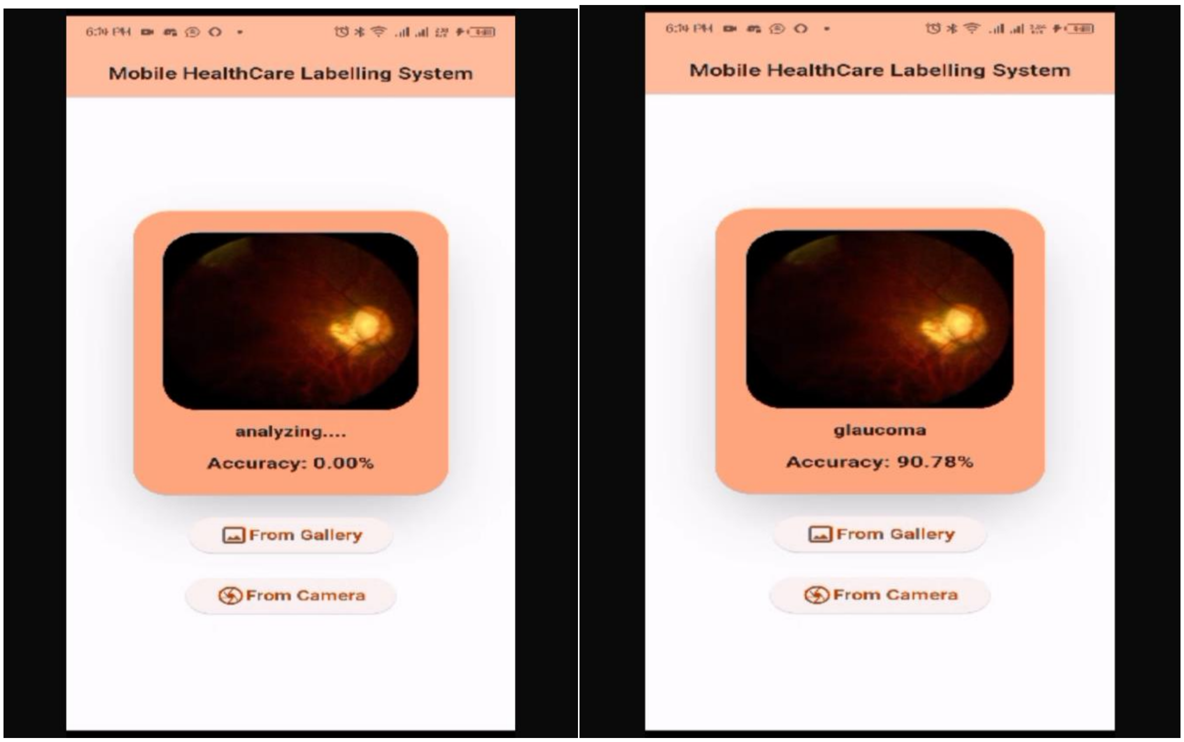
Figure 6: The mobile application software developed for health care labelling



(a) Data upload (b) classification and labelling

Figure 7: Result of the system for classification of diabetes retinopathy

The Figure 7 (a) presented the upload of a real-life test data of diabetes retinopathy image upload on the software, while the Figure 7(b) showcased the classification and labelling results. With 99.3% accuracy. This high accuracy rate suggests that the software is very effective in accurately identifying and labelling diabetic retinopathy images. This result is significant as diabetic retinopathy is a serious complication of diabetes and early detection through image analysis can be crucial for timely intervention and treatment. The Figure 8 presents the result with Glacoma test data.



(a) Data upload (b) Classification result

Figure 8: Test result with glaucoma data

The results of testing the software using glaucoma-related data are shown in Figure 10. The technique of loading this data into the software is probably shown in Figure 10(a). It is reported that features from the imported data were extracted using Mobile-Net, a convolutional neural network architecture designed for mobile devices. For additional analysis, these features were subsequently fed into a trained clustered-based neural network. The results of this analysis are displayed in Figure 10(b), which demonstrates that the software accurately identified and categorized the data with a 90.7% accuracy rate. The software's ability to differentiate between various glaucoma symptoms using the retrieved features is demonstrated by the remarkably high accuracy rate. This finding is significant in the context of glaucoma, a progressive eye disease that, if left untreated, can result in irreversible vision loss. The implementation of effective treatment measures to prevent or slow down vision impairment is contingent upon the early

detection of glaucoma. Consequently, the software's high degree of accuracy in classifying glaucoma-related data points to its possible use as an ophthalmology diagnostic tool.
Cross validation results of the experimental test was reported in the Table 2.

Table 2: Ten-fold cross experiment of the results considering classification accuracy

Fold	Diabetes retinopathy	Glaucoma	Normal	Cataract
1	99.30	90.78	97.80	98.34
2	99.13	92.65	95.98	98.55
3	99.50	90.34	97.58	98.64
4	99.28	91.85	97.38	98.21
5	99.33	90.86	96.45	98.09
6	99.39	90.98	97.74	98.45
7	99.53	90.83	96.24	98.39
8	99.65	90.55	97.45	98.97
9	99.45	90.14	97.23	98.46
10	99.65	90.28	96.54	98.21
Avg.	99.421	90.926	97.039	98.431

Table 2 presented the result of the validation of the software developed in ten-fold considering the four classes of health care images. From the results, it was observed that average all the model recorded above 90% classification accuracy. From the results, it was observed that the model performs best with the classification of diabetes retinopathy, recording 99.42%, while overall the total average accuracy of classification is 96.45%. To validate the model, comparative analysis with existing model was performed and the results presented in Table3;

Table 3: Comparative analysis

Author	**Technique**	**Accuracy (%)**
Bitto et al. (2022)	VGG	95.48
	ResNet	95.78
	Inception-v3	97.08
Nazir et al. (2019)	NB	81.53
	DT	85.81
	RF	86.63
	ANN	86.98
Bodapati et al. (2021)	DNN	84.21
Khan et al. (2021)	CNN	90
Sarki et al. (2022)	CNN	90
Normal	MobileNet + Clustered Neural network	97.039
Cataract		98.431
Diabetes retinopathy		99.421
Glaucoma		90.926

Table 3 presented a comparative analysis of the model developed with Mobile-Net and clustered based neural network for health care classification and labelling against other existing algorithms considering accuracy. From the results, it was observed that new model recorded the highest classification accuracy for three classes of diabetes retinopathy with 99.421%, cataract with 98.43%, and normal data with 97.04%. The reason for this high score was due to the effectiveness of the bottleneck which utilized the depth-wise and pointwise to extract enough features from the health care image input, thus allowing the clustered based neural network to learning enough features and return high classification score as recorded.

5. CONCLUSION

This research develops a deep learning model specifically tailored for automated data labelling in healthcare, with a primary focus on enabling personalized diagnosis of healthcare challenges, particularly eye diseases. By leveraging advanced machine learning techniques, the aim is to revolutionize diagnostic process, ultimately leading to improved patient outcomes and enhanced quality of care. The core objectives of the research include the development of an integrated deep learning framework designed to improve efficiency, scalability, and reliability in health care data labelling processes. Through careful design and implementation, the framework aims to streamline workflows, minimize human error, and standardize diagnostic outcomes, thereby facilitating rapid and precise diagnosis of eye diseases. Central to the research objectives is the evaluation of the deep learning model's performance and integration within existing healthcare systems. By validating its efficacy through rigorous testing and assessment, the aim is to pave the way for widespread adoption and implementation of the framework in clinical settings, ultimately enhancing the diagnostic capabilities of healthcare professionals and improving patient care outcomes.

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