High-Performance Intelligent System for Real-Time Medical Image Using Deep Learning and Augmented Reality

G. A. Senthil, R. Prabha, R. Rajesh Kanna, G. Umadevi Venkat, and R. Deepa

Abstract Evolving new diseases demand the need for technology to identify the disease in an effective way. Medical imaging in the field of disease identification helps to identify the disease by scanning the human parts, thereby preventing the increased rate of deaths. Deep learning algorithms make it easier to identify and analyze disease efficiently through medical imaging. The high performance of these models is needed for the disease to be predicted with accurate results. The prediction rate of the disease can be increased by the efficient use of deep learning modules and algorithms. This research involves the use of deep learning models in identifying brain hemorrhage and retinopathy diseases through deep learning algorithms. The deep learning algorithms AlexNet and convolutional neural network (CNN) with the accuracy of 90% and 96%, respectively, are employed for the detection of brain hemorrhage, and ResNet-50 and CNN with accuracy of 70% and 92%, respectively, are used for the identification of retinopathy. The output of the model is displayed using augmented reality (AR), which makes it interactive for the user to analyze the results. The AR display is achieved using the unity engine along with the Vuforia package and using the barracuda package for importing the deep learning model into

G. A. Senthil (✉)
Department of Information Technology, Agni College of Technology, Chennai, India
e-mail: senthilga@gmail.com

R. Prabha
Department of Electronics and Communication Engineering, Sri Sai Ram Institute of Technology, Chennai, India
e-mail: r.praba05@gmail.com

R. Rajesh Kanna · G. Umadevi Venkat
Department of Computer Science and Engineering, Agni College of Technology, Chennai, India
e-mail: rkanushaquafarms@gmail.com

G. Umadevi Venkat
e-mail: deviuma1909@gmail.com

R. Deepa
Department of Computer Science and Engineering, Vels Institute of Science and Technology and Advanced Studies, Chennai, India
e-mail: deepar.se@velsuniv.ac.in

P. P. Joby et al. (eds.), *IoT Based Control Networks and Intelligent Systems*, Lecture Notes in Networks and Systems 789, https://doi.org/10.1007/978-981-99-6586-1_8

unity. Thus, by increasing the accuracy rate of the system, this research demonstrates the high performance of the intelligent system.

Keywords Deep learning · Convolutional neural network (CNN) · AlexNet · ResNet-50 · Medical imaging · Brain hemorrhage · Eye retinopathy · Open neural network exchange (ONNX) · Augmented reality (AR)

1 Introduction

The prevalence of diseases around the world urges the need for a high-performance intelligent system that detects the presence of various diseases through medical imaging [1]. This can be achieved by developing various deep learning models. Intelligent models that are used in the detection of such diseases must be efficient and must result in efficient output. This research involves the detection of brain hemorrhages and eye retinopathy through various deep learning algorithms and the results of which are displayed using augmented reality [2].

Brain hemorrhage is a condition caused by the blood vessels in the brain. Its presence can be sensed through various medical imaging techniques. Deep learning algorithms AlexNet and convolutional neural network (CNN) are used in the detection process. Medical imaging techniques like CT scans and MRI can be utilized to identify brain bleeding using deep learning models. CNNs are one method for analyzing the images and locating areas that are suggestive of brain bleeding [25].

Retinopathy is a disease caused in the retina of the eye due to complications of diabetes affecting the blood vessels of the eye [27–29]. There are several ways in which deep learning models can be used for the detection of retinopathy. One common approach is to use CNNs to analyze images of the retina and identify patterns or features that are characteristics of retinopathy. One way to do this is to use a dataset of retinal images that have been labeled as either healthy or unhealthy to train a CNN to classify new images as healthy or unhealthy based on their visual characteristics [26]. This type of deep learning model can be used to detect retinopathy at an early stage, potentially enabling earlier diagnosis and treatment. The intelligent system deployed here uses CNN and ResNet-50 as deep learning algorithms. The algorithms used for the identification of these conditions in the human body yield the best and most efficient accuracy [16–18]. A major part of these intelligent systems is diagnosing the disease at the earliest stage possible [19–23].

To help the augmented reality (AR) system comprehend the user's environment, deep learning can be employed. To recognize items or landmarks in the surroundings, for instance, to evaluate images taken by the user's webcam in real time, a deep learning model might be used. The user's vision of the real world might then be supplemented with digital information using this information. Another method is to employ deep learning to help the AR system comprehend and react to the user's motions and activities. To translate the user's motions or facial expressions as orders for the AR system, a deep learning model may be utilized, for instance. The trained deep learning model is extracted as the h5 model in order to use that in unity [3].

The Keras model is then converted to the Open Neural Network Exchange (ONNX) model thereby deployed and executed in unity using the barracuda package. ONNX is the model used for importing the deep learning models into tools for using the models without changing its nature [9, 10]. To display the results as an augmented reality object, Vuforia SDK is employed. The output shows the accuracy along with the scanned image for the user convenience [11–15].

2 Related Works

Balasooriya et al. [4] developed an intelligent system with deep learning models for the prediction of brain hemorrhage. The work dealt with the recognition and prediction of brain hemorrhage disease using deep learning algorithms and performed performance metrics analysis for the analysis of the obtained output. The deep learning algorithm used for the research was an artificial neural network with the feature of finding the classification of the diagnosed condition of the hemorrhage. The study explored the potential for classifying brain hemorrhage utilizing segmentation process from CT scan images created using the watershed approach, then providing the shared information from the retrieved brain CT image.

Hidayatullah et al. [5] in research on the hemorrhage detection in the brain used a mathematical model for the diagnosis with watershed method, and the binary values of each phase was used for the calculation of the average error found in the entire research. As the work uses mathematical models over the deep learning models, it efficiently uses the techniques for the prediction of the system. The computation of the brain region from the testing process has an average inaccuracy of 1.13%. Regarding the test, the average deviation in calculating the hemorrhage area is 11.17%.

Singh Gautam et al. [6] proposed a solution for the detection of eye retinopathy using an automated system with MATLAB algorithms and with various efficient mathematical models, with the simplest approach for early diabetic retinopathy (DR) detection, and preventing irreversible vision loss in patients was the suggested technique, which requires only a fundus camera as well as a system software with MATLAB installed. The accuracy obtained was comparatively low compared to the existing results.

Masood et al. [7], in the transfer learning-based system for the identification of the eye retinopathy in the retina of the human eye, used neural networks like ImageNet algorithm in the process of the detection of the condition. The deep learning algorithm used for the detection purpose of the system efficiently analyzes the system of the input of the scanned images which are first fed into the system and trained with the ImageNet algorithm and with the output the model which is retrained with the same algorithm, thus attaining the efficient system for the detection.

Brunet et al. [8] offered a technique for learning complicated elastic permanent deformation using a deep neural system and a method of finite elements with the goal of enabling augmented reality during liver surgery, which is based on the U-Net design, constructed solely from physiologically models of an organ division performed prior to surgery. It was claimed to provide an efficient system with the accuracy that matches the accuracy of the FEM solution. The system thus resulted in the simulation of the results in the augmented reality in an effective way.

3 Dataset Description

For detecting the brain hemorrhage, the CT scan images of the patient's head are collected. The dataset contains 2000 scanned images of brains, and the dataset also contains a CSV file that provides the metadata of the images whether the patient is affected by brain hemorrhage or not. It contains only two classes whether the patient is affected by the hemorrhage or not.

The other dataset used for the detection of diabetic retinopathy is a large set of high-resolution images that contains images of eye from different angles which are labeled by the clinic with five different scales from no DR to mild, moderate, severe, and proliferative doctor. The dataset contains approximately 3500 images.

4 Methodology

The high-performance medical imaging works by getting an input image from the user which is then preprocessed and classified based on the type of image. Following the categorization of the disease, the image is sent to high-performance deep learning modules, which determine whether the patient is affected by the specific illness or not. Lastly, the outcome is depicted in augmented reality (Fig. 1).

4.1 Convolutional Neural Network

4.1.1 Deep Learning

A subunit of machine learning algorithms that are highly excellent at pattern recognition but typically require a large amount of data is deep learning. Deep learning is effective in image object recognition because it employs three or more layers of artificial neural networks, each of which is in charge of extracting one or more characteristics from the image. Four convolutional layers and four pooling function layers make up the convolutional neural network model. It is a multi-layer perceptron with a convolution operation at the output layer, as it is typical. Because each neuron in the preceding layer interacts with every neuron in the layer after it, the phrase "Fully Connected" was coined. There are two Fully Connected layers and a SoftMax

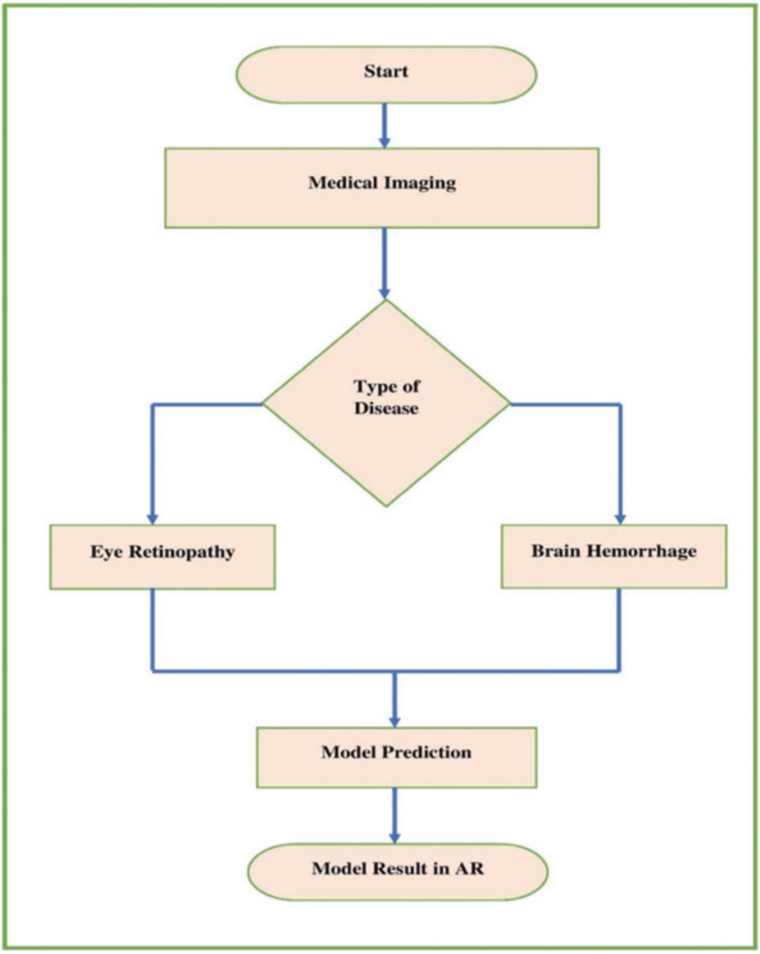

Fig. 1 Flowchart of medical imaging using AR

layer with varied color leaf classes. The input image is a color retina image with a resolution of 32 × 32 pixels (Fig. 2).

4.1.2 Constructing a Convolutional Neural Network

Once preprocessing and splitting the dataset are performed, the neural network can be built. Three convolutional layers with a maximum grouping of 2 × 2 are used [24]. Though several architectures for deep learning are being investigated to handle diverse problems, CNNs are now the most prominent deep learning design categorizations for healthcare imaging. Convolutional neural network is a sort of artificial deep

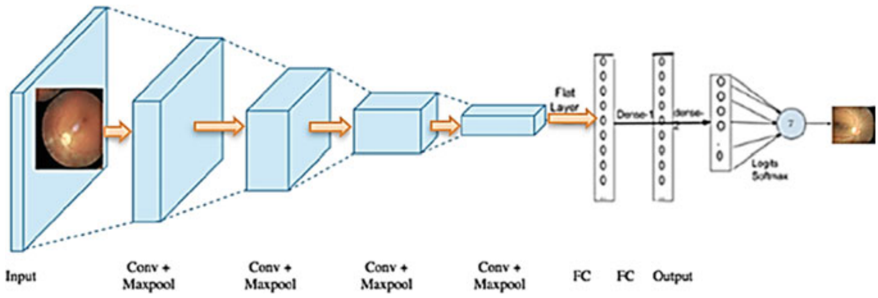

Fig. 2 Architecture of AlexNet—CNN algorithm

learning neural network. It is used in the fields of image recognition and computer vision.

4.1.3 Max Pooling

CNN usually employs the max pooling strategy to shrink the dimensions of the extracted features while preserving crucial data. It is a method for reducing image size by finding the maximum value of pixels from the grid. This also helps to reduce overfitting and generalizes the model. The following example demonstrates how the maximum pool of 2×2 works. The largest value found within every non-overlapping rectangular zone is chosen as the result of max pooling, which divides the input mapping into regions. By downsampling the feature maps and shrinking their spatial extent, max pooling aims to decrease computational complexity and overfitting. As the greatest value inside a pooling zone signifies the existence of a certain feature independent of its exact placement inside the region, it also increases the network's resistance to little fluctuations in the data. Since the brain tumor will be very small in images and it is hard to find the affected part, max pooling is used to reduce the size of the image and to gather every feature to make the prediction more accurate (Fig. 3).

4.2 Brain Hemorrhage

To develop a model, the dataset must be balanced. So, the amount of data count in each class is checked. Here, the dataset is balanced, but it contains only 2000 images which is very less for developing a deep learning model. To handle this issue, an image data generator [8] is used, which is an open-source library by TensorFlow, to generate more data with the help of the existing dataset. In the exploratory data analysis [9] phase, the images with different labels are visualized for analyzing the image size and image quality.

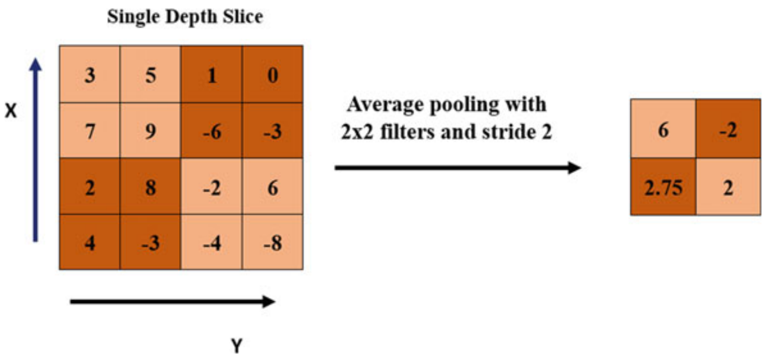

Fig. 3 2 × 2 max pooling

Figure 4 shows the CT scans of patients affected by brain hemorrhage. Here, the images in the datasets vary a lot, and to notice the difference clearly, matplotlib is used, which visualizes the data in a more custom way to understand it easier. The images show how much the patient is affected by the brain hemorrhage with a good quality of scan that ensures the reliability of the images for developing a detection model.

From Fig. 5, it is clear that the dataset contains images of different sizes which affects the model development. To overcome these issues, the images are resized to a fixed size, but expanding the images will significantly reduce the image quality or remove the images. To avert this, the image size is reduced to 128 pixels instead of 134. Now, to increase the model accuracy, the dataset is enhanced by adding flipped images irrespective of the direction which increase the model performance. Even though the dataset size is increased by adding flipped images, it is not enough to create a model that accurately detects the hemorrhage. So, using image data generator, new images are created by resizing, zooming, and rotating the existing images which will help in creating an accurate model for the detection of hemorrhage.

4.3 Eye Retinopathy

The dataset contains five different classes of eye retinopathy that range from no retinopathy, mild, moderate, severe, and proliferative retinopathy. The dataset is huge; it contains 35,000 images and out of which only 10,000 images are labeled. The diabetic-affected patients will have a defect in eye retina which causes severe issues in eyes visibility and also may lead to blindness. This module helps to identify the eye retina's affected level and help patients to analyze the disease earlier.

The dataset contains different classes, but the images are not evenly distributed among all the classes. Here, the patients who are affected by retinopathy are high and moderate affected people's data ranks second, but all the other classes have only

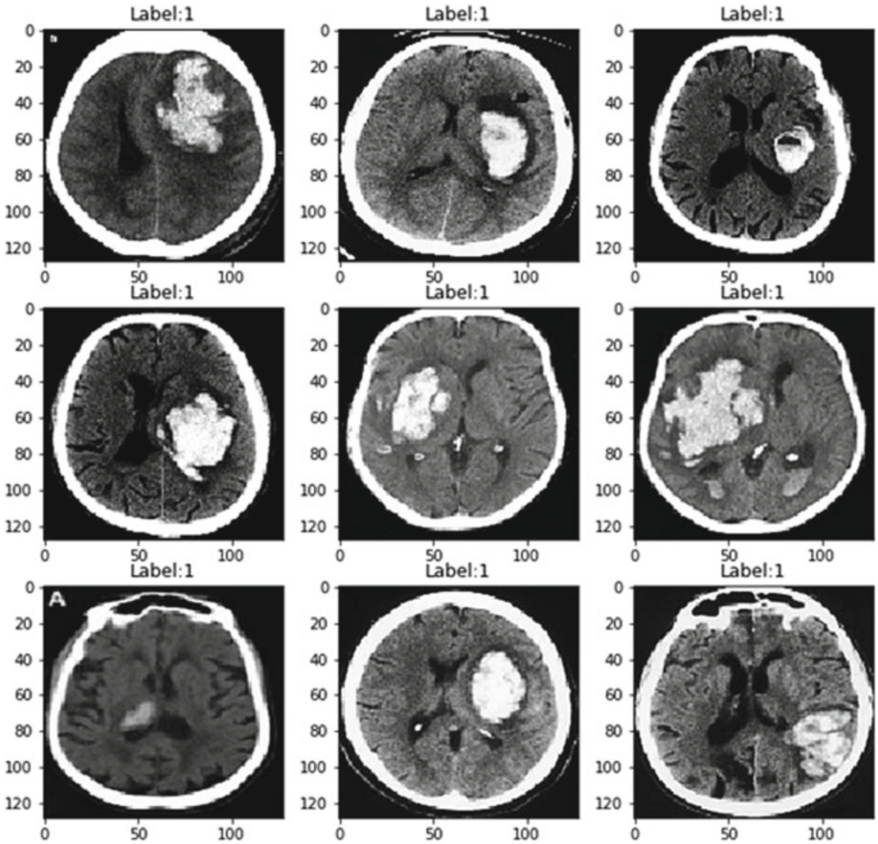

Fig. 4 CT scan images of patients affected by brain hemorrhage

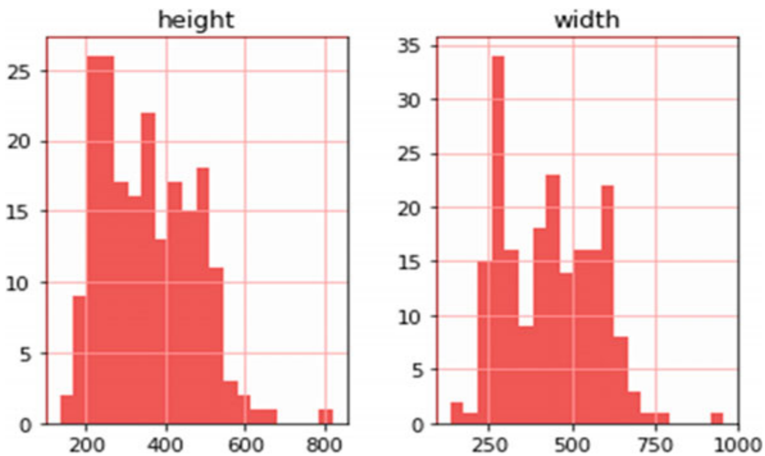

Fig. 5 Graph showing the height and width of different images in the dataset

minimum amount of data which creates a highly unstable dataset. Figure 6 shows that the dataset is highly imbalanced which leads to reduced model accuracy.

For balancing the dataset, a Python script is used which oversamples the data and produces images equally for each class. In Fig. 7, the imbalanced dataset is balanced for all the classes by applying undersampling and oversampling techniques apparently for specific classes as needed. Now, finding the difference in each class of the images is explored, which is shown in Fig. 8.

The above image shows the dataset from different classes during exploratory data analysis. The image contains images of eyes in different angles and with different color shades. Since the image contains different color shades which affects the efficiency of the model learning, the data is converted to gray scale and the edges of the images are also detected that will make the image more qualified for feeding as a training dataset. After performing all the steps, the images are now passed for model development which takes all the images to develop an adequate model. Since

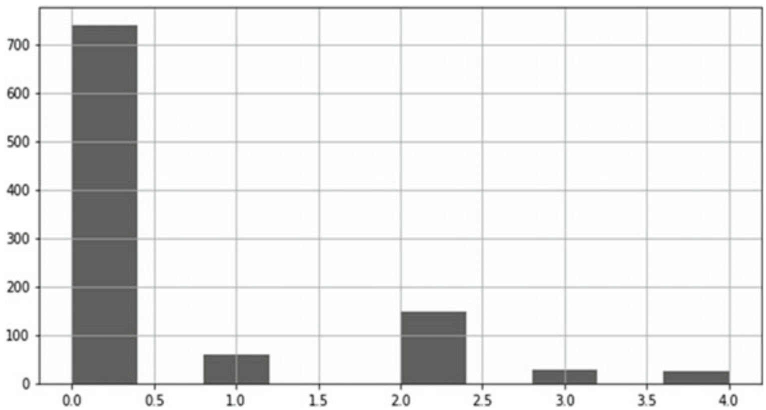

Fig. 6 Graph showing images count in each classes

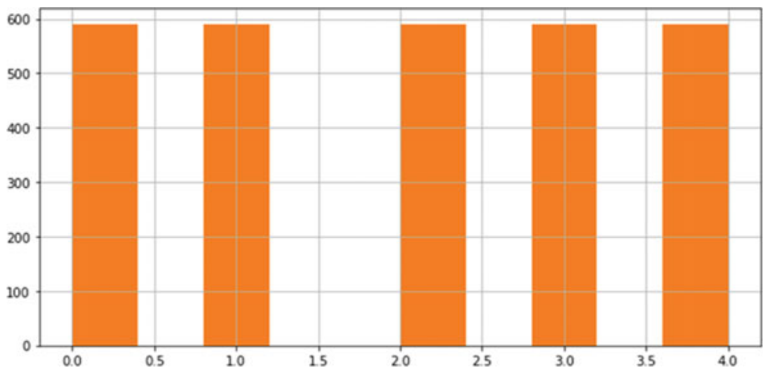

Fig. 7 Images in each classes after oversampling the dataset

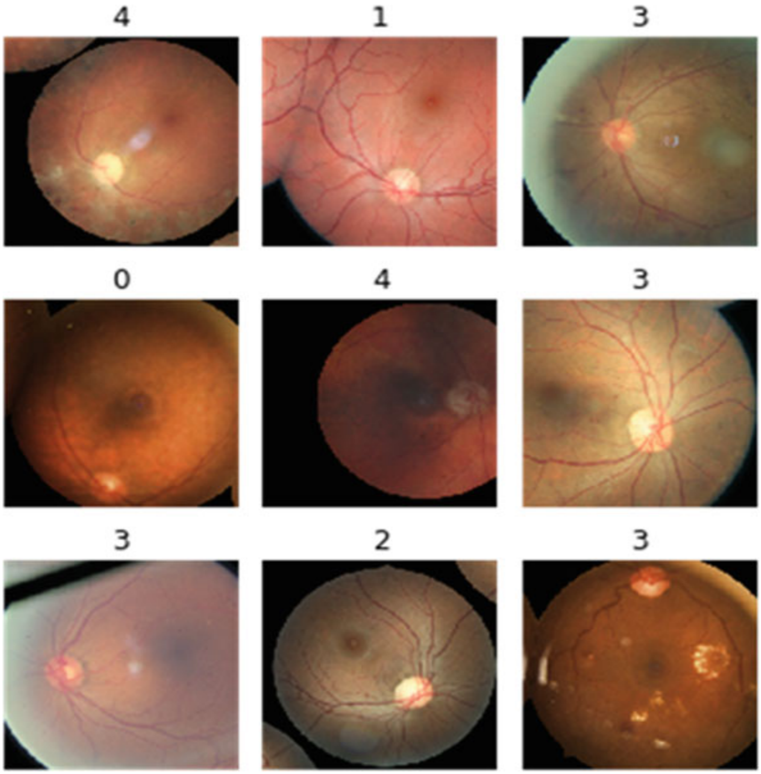

Fig. 8 Images for different classes

the dataset is balanced and contains enough data for model development, it is not necessary to perform any feature engineering techniques. Now, the dataset can be split into training and testing groups and used for model building.

4.4 Architectural Diagram

Figure 9, the development of the model, is deployed in unity for the augmented reality output. For this purpose, the model fed is first extracted as a Keras model. The Keras model is an h5 file which is then converted into the ONNX model which is done by importing the libraries that are essential for the development of the model.

First, an input image is obtained from the user, then the system finds whether it is a brain tumor or eye retinopathy, and then moves on to the image processing stage, where the image is processed. Next, the processed brain tumor images move to the AlexNet model and the eye retinopathy to the ResNet model. This model is then fed into the unity engine for the further process of visualizing the output through

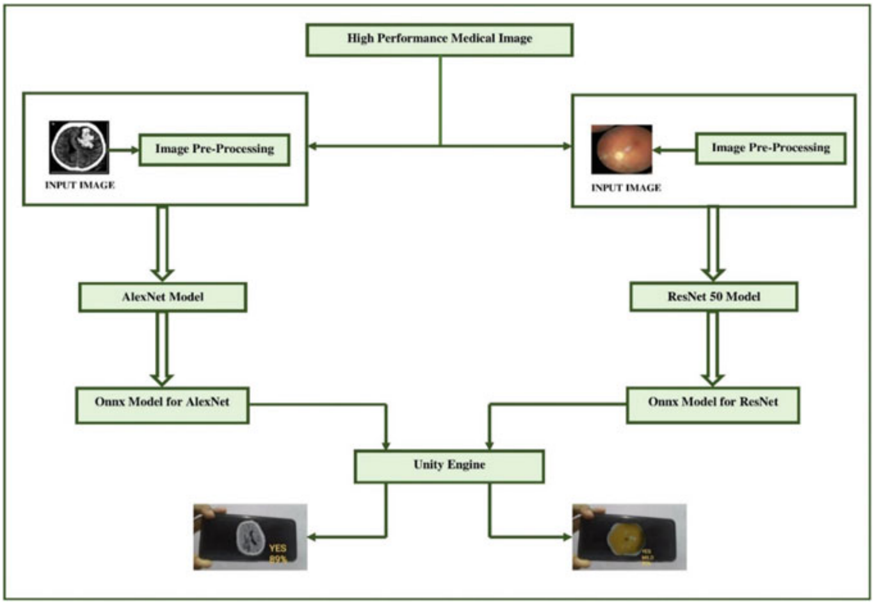

Fig. 9 Architectural diagram for high-performance medical imaging

augmented reality. By importing the barracuda package for the visualization process, the AR image can be seen accurately on the predicted image of the disease, as shown in Fig. 10. The developed model cannot be directly imported into the unity engine. The model thus trained is converted into the ONNX model, and using the barracuda package, which is a package that supports deep learning systems to be implemented in the unity engine, the model is imported.

The developed deep learning model is converted into an ONNX model (which is a model that makes the artificial intelligence models to adopt any framework). The converted ONNX model is then imported into unity. Using Vuforia, the object is trained to be placed in the mid-air or ground plane. The output of the model is connected with Vuforia to get the intended result.

Fig. 10 Augmented reality output for both models

5 Experiment

To develop a model for a brain hemorrhage, the dataset must be separated as test and train data. The train data is used to create a model, and the test data is used to test the model after development. Since the data contains only two classes, a simple conventional neural network can be used for model building. The model is built with three hidden layers, with max pooling, and global average pooling, which finds the difference in small areas rather than comparing it with the entire image which will be helpful to find the hemorrhage in the brain.

$$[n, n, nc] * [f, f, nc] = \left[\left[\frac{n + 2p - f}{s} + 1\right], \left[\frac{n + 2p - f}{s} + 1\right], nf\right] \tag{1}$$

Equation 1 shows the working of conventional neural network. The sigmoid activation function is used since it is a binary classification problem. The model has to produce very minimal false positive output because the false positive outputs will lead to risking the patient's life. So, an imbalanced dataset is used that reduces the possibilities of false negative outputs. Finally, the model produces 90% accurate models.

$$\begin{aligned} &(\text{CNN} \rightarrow \text{RN} \rightarrow \text{MP})^2 \rightarrow (\text{CNN}^3 \rightarrow \text{MP}) \\ &\rightarrow (\text{FC} \rightarrow \text{DO})^2 \rightarrow \text{Linear} \rightarrow \text{SoftMax} \end{aligned} \tag{2}$$

Here,

CNN	Convolutional layer (with ReLU activation).
RN	Local response normalization.
MP	Max pooling.
FC	Fully Connected layer (with ReLU activation).
Linear	Fully Connected layer (without activation).
DO	Dropout.

The above equation shows the working of AlexNet, where the CNN is processed with pooling techniques and activation function to create a seamless architecture.

$$y = f(x, W) + x \tag{3}$$

Here,

y	Final output.
W	Weights.
x	Input.
$f(x, W)$	Function mapping from input to weights.

Figure 11 shows that the final output of the mappings is predicted using the above equation with the function that accepts the inputted value and weights as input added to the input value.

The data is trained with AlexNet [11] algorithm which is a type of CNN which contains five conventional layers, three max pooling layers, two normalization layers, and one SoftMax layer, which helps to detect the minor difference in the images and classify based on it. Since the AlexNet contains eight layers, it performs detection in a smaller area better than other algorithms. The model produced an accuracy of 96% which will detect the hemorrhage better than the CNN [10] model (Fig. 12).

The resultant model development phase of eye retinopathy CNN is implemented in matplotlib and used for creating a model that classifies the type based on the dataset. To perform the classification using CNN, the model is built with five layers out of which three hidden layers with SoftMax activation function and Adam optimizer.

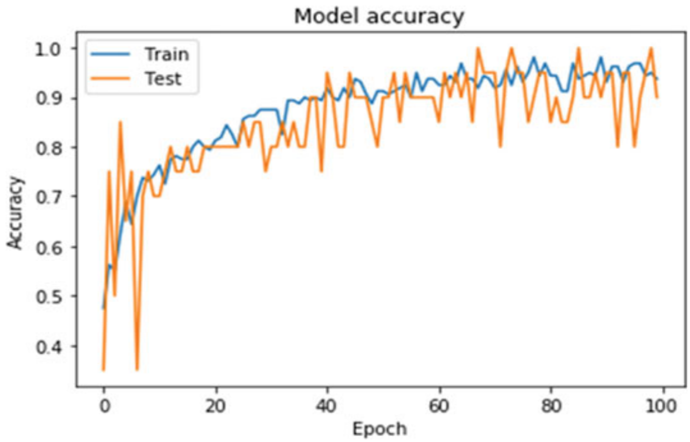

Fig. 11 Model accuracy for training and test data

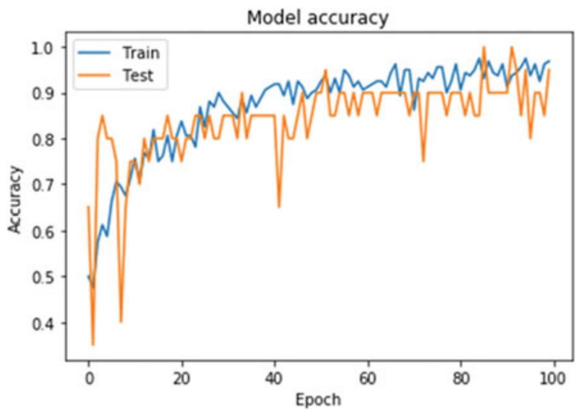

Fig. 12 Model accuracy for train and test data with AlexNet algorithm

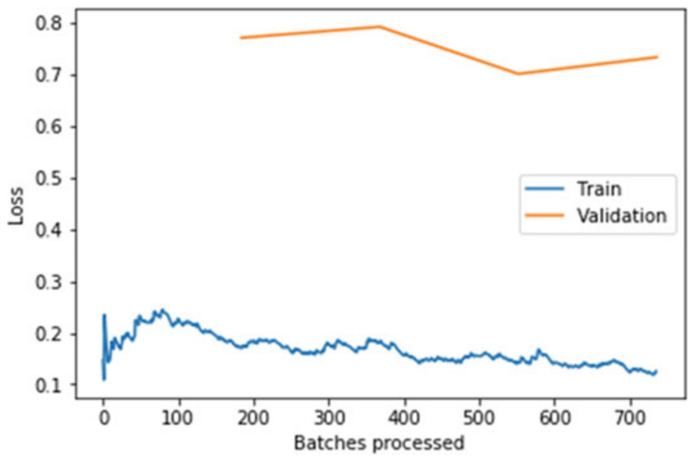

Fig. 13 Model accuracy and loss with respect to data

The model is trained with 40 epochs, and the loss decreases gradually and finally produces an accuracy of 70%. Since the model is used for medical imaging, the accuracy is not enough for real-time application.

By using transfer learning, a better model can be built. Here, ResNet-50 is used which is a widely used transfer learning model which is pretrained with ImageNet dataset, and it also makes the training easier with the help of fast artificial intelligence. Finally, it produces an accuracy of 92% with minimal loss. The graph in Fig. 13 shows that the model is learning in a faster way, and adequate results are produced with the training dataset.

6 Results and Discussion

The results of the deep learning models were much more efficient. For the brain hemorrhage model, the algorithms used are CNN and AlexNet which yielded the accuracy of 90% and 96%, respectively, and in case of eye retinopathy, the deep learning model is developed with the deep learning algorithms including CNN and ResNet-50 [12] with accuracy of about 70% and 92%, respectively. These are compared with the existing deep learning models developed for the same purpose and identified with high-performance models with high-performance algorithms. Tables 1 and 2 results are obtained from the deep learning models.

Since the model is trained with huge dataset, a reasonable accuracy that is above 91% is produced. The model will produce a reliable output in real-time use cases. Large datasets are employed to treat the model, and feature engineering procedures as well as other model tuning methods, including max pooling, have been heavily focused. The performance of the model can be improved by training the model with

Table 1 Brain hemorrhage

Algorithm	Accuracy (%)
CNN	90
AlexNet	96

Table 2 Eye retinopathy

Algorithm	Accuracy
CNN	70
ResNet-50	92

more datasets with a GPU setup which will improve the model learning rate that improves the performance of the model.

The results of the model are displayed using augmented reality via unity based on computer vision by deploying the model in the unity using barracuda package, and the output is displayed along with the accuracy of the detection of the deep learning model developed. The model prediction is obtained by developing a deep learning model with AlexNet and ResNet, fine-tuning both models for classifying tumors and retinopathy, and testing the model, thus achieving an accuracy of 96% and 92%, respectively, throughout testing.

7 Conclusion

The need of diagnosing the critical body conditions of the humans is crucial as it reduces the chance of death due to such cases. An intelligent system is developed with high performance, which involves the use of deep learning algorithms with high performance and accuracy. Two conditions are used for the development of a high-performance intelligent system, and various deep learning algorithms are used to compare the results. The accuracy of the CNN and AlexNet algorithms for the detection of brain hemorrhage resulted in 90 and 96%. The detection of eye retinopathy using the deep learning algorithms resulted in 70 and 92% accuracy. The models thus resulting with the efficient and accurate output proved the high performance of the intelligent system.

8 Future Work

In the future, the medical imaging can be enhanced by using more real-time dataset for brain hemorrhage detection, and the research work can be expanded by combining all the other disease detection modules in a single application. In eye retinopathy, different algorithms can be used to create more accurate classification using machine learning algorithm. The patients can be screened by a separate model that detects the problem, and then it is further transferred to these models for accurate results. The results of simulation can be the extended and integrated mixed reality combination of augmented reality and virtual reality using 3D models for better visualization.

References

1. Wang B, Xu K, Song P, Zhang Y, Liu Y, Sun Y (2021) A deep learning-based intelligent receiver for OFDM. In: 2021 IEEE 18th international conference on mobile ad hoc and smart systems (MASS), pp 562–563. https://doi.org/10.1109/MASS52906.2021.00075
2. Min K, Kim H, Huh K (2019) Deep distributional reinforcement learning based high-level driving policy determination. IEEE Trans Intell Vehic 4(3):416–424. https://doi.org/10.1109/TIV.2019.2919467
3. Anwar A et al (2022) Image aesthetic assessment: a comparative study of hand-crafted & deep learning models. IEEE Access 10:101770–101789. https://doi.org/10.1109/ACCESS.2022.3209196
4. Balasooriya U, Perera MUS (2011) Intelligent brain hemorrhage diagnosis system. In: 2011 IEEE international symposium on IT in medicine and education, pp 366–370.https://doi.org/10.1109/ITiME.2011.6132126
5. Hidayatullah RR, Sigit R, Wasista S (2017) Segmentation of head CT-scan to calculate percentage of brain hemorrhage volume. In: 2017 international electronics symposium on knowledge creation and intelligent computing (IES-KCIC), pp 301–306. https://doi.org/10.1109/KCIC.2017.8228603
6. Singh Gautam A, Kumar Jana S, Dutta MP (2019) Automated diagnosis of diabetic retinopathy using image processing for non-invasive biomedical application. In: 2019 international conference on intelligent computing and control systems (ICCS), pp 809–812. https://doi.org/10.1109/ICCS45141.2019.9065446
7. Masood S, Luthra T, Sundriyal H, Ahmed M (2017) Identification of diabetic retinopathy in eye images using transfer learning. In: 2017 international conference on computing, communication and automation (ICCCA), pp 1183–1187. https://doi.org/10.1109/CCAA.2017.8229977
8. Brunet JN, Mendizabal A, Petit A, Golse N, Vibert E, Cotin S (2019) Physics-based deep neural network for augmented reality during liver surgery. In: Medical image computing and computer assisted intervention—MICCAI 2019. MICCAI 2019. Lecture notes in computer science, vol 11768. Springer
9. Kim K, Myung H (2018) Autoencoder-combined generative adversarial networks for synthetic image data generation and detection of jellyfish swarms. IEEE Access 6:54207–54214
10. Chen J, Kuang J, Zhao G, Huang DJH, Young EF (2020) PROS: a plug-in for routability optimization applied in the state-of-the-art commercial EDA tool using deep learning. In: 2020 IEEE/ACM international conference on computer aided design (ICCAD). IEEE, pp 1–8
11. Matsumoto T, Yokohama T, Suzuki H, Furukawa R, Oshimoto A, Shimmi T, Matsushita Y, Seo T, Chua LO (1990) Several image processing examples by CNN. In: IEEE international workshop on cellular neural networks and their applications. IEEE, pp 100–111
12. Xiao L, Yan Q, Deng S (2017) Scene classification with improved AlexNet model. In: 2017 12th international conference on intelligent systems and knowledge engineering (ISKE). IEEE, pp 1–6
13. Mukti IZ, Biswas D (2019) Transfer learning based plant diseases detection using ResNet50. In: 2019 4th international conference on electrical information and communication technology (EICT), Khulna, Bangladesh, pp 1–6. https://doi.org/10.1109/EICT48899.2019.9068805

14. Navadia NR, Kaur G, Bhardwaj H (2021) Brain hemorrhage detection using deep learning: convolutional neural network. In: Information systems and management science: conference proceedings of 4th international conference on information systems and management science (ISMS). Springer International Publishing, Cham, pp 565–570
15. Lalonde J-F (2018) Deep learning for augmented reality. In: 2018 17th workshop on information optics (WIO), Quebec, QC, Canada, pp 1–3.https://doi.org/10.1109/WIO.2018.8643463
16. Akgul O, Penekli HI, Genc Y (2016) Applying deep learning in augmented reality tracking. In: 2016 12th international conference on signal-image technology & internet-based systems (SITIS), Naples, Italy, pp 47–54. https://doi.org/10.1109/SITIS.2016.17
17. Varma RB, Umesh IM, Upendra RS (2021) Augmented reality and deep learning in e-learning—a new approach. Int J Appl Eng Res 16:749–751
18. Shone N, Ngoc TN, Phai VD, Shi Q (2018) A deep learning approach to network intrusion detection. IEEE Trans Emerg Top Comput Intell 2(1):41–50. https://doi.org/10.1109/TETCI.2017.2772792
19. Li Y, Hao C, Zhang X, Liu X, Chen Y, Xiong J, Hwu WM, Chen D (2020) EDD: efficient differentiable DNN architecture and implementation co-search for embedded AI solutions. In: 2020 57th ACM/IEEE design automation conference (DAC). IEEE, pp 1–6
20. Devika R, Avilala SV, Subramaniyaswamy V (2019) Comparative study of classifier for chronic kidney disease prediction using Naive Bayes, KNN and random forest. In: 2019 3rd international conference on computing methodologies and communication (ICCMC). IEEE, pp 679–684
21. Atwany MZ, Sahyoun AH, Yaqub M (2022) Deep learning techniques for diabetic retinopathy classification: a survey. IEEE Access
22. Singh SP, Wang L, Gupta S, Gulyas B, Padmanabhan P (2020) Shallow 3D CNN for detecting acute brain hemorrhage from medical imaging sensors. IEEE Sens J 21(13):14290–14299
23. Balasooriya U, Perera MS (2012) Intelligent brain hemorrhage diagnosis using artificial neural networks. In: 2012 IEEE business, engineering & industrial applications colloquium (BEIAC). IEEE, pp 128–133
24. Prabha R, Senthil GA, Razmah M, Akshaya SR, Sivashree J, Cyrilla Swathi J (2023) A comparative study of SVM, CNN, and DCNN algorithms for emotion recognition and detection. In: Jacob IJ, Kolandapalayam Shanmugam S, Izonin I (eds) Data intelligence and cognitive informatics. Algorithms for intelligent systems. Springer, Singapore. https://doi.org/10.1007/978-981-19-6004-8_64
25. Prabha SGAR, Razmah M, Sridevi S, Roopa D, Asha RM (2022) A big wave of deep learning in medical imaging—analysis of theory and applications. In: 2022 6th international conference on intelligent computing and control systems (ICICCS), pp 1321–1327. https://doi.org/10.1109/ICICCS53718.2022.9788412
26. R-Prabha M, Prabhu R, Suganthi SU, Sridevi S, Senthil GA, Babu DV (2021) Design of hybrid deep learning approach for covid-19 infected lung image segmentation. J Phys Conf Ser 2040(1):012016. https://doi.org/10.1088/1742-6596/2040/1/012016
27. Prabha R, Senthil GA, Lazha A, Vijendra Babu D, Roopa MD (2021) A novel computational rough set based feature extraction for heart disease analysis. In: I3CAC 2021: proceedings of the first international conference on computing, communication and control system, I3CAC 2021, 7–8 June 2021. European Alliance for Innovation, Bharath University, Chennai, India, p 371. https://doi.org/10.4108/eai.7-6-2021.2308575
28. Prabha R, Anandan P, Sivarajeswari S, Saravanakumar C, Vijendra Babu D (2022) Design of an automated recurrent neural network for emotional intelligence using deep neural networks. In: 2022 4th international conference on smart systems and inventive technology (ICSSIT), pp 1061–1067. https://doi.org/10.1109/ICSSIT53264.2022.9716420
29. Prabha R, Razmah M, Veeramakali T, Sridevi S, Yashini R (2022) Machine learning heart disease prediction using KNN and RTC algorithm. In: 2022 international conference on power, energy, control and transmission systems (ICPECTS), Chennai, India, pp 1–5. https://doi.org/10.1109/ICPECTS56089.2022.10047501