EYE CATARACT DISEASE DETECTION BY USING TRANSFER LEARNING

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ABSTRACT:

Cataract, a leading cause of blindness worldwide, necessitates early and accurate diagnosis for effective treatment. In recent years, deep learning techniques have shown promising results in medical image analysis, particularly in the field of ophthalmology. This study proposes a comprehensive approach for the detection of eye cataract disease utilizing Convolutional Neural Networks (CNN's), including Dense-net, Res-net, and VGG16 architectures. The proposed methodology involves preprocessing of eye images followed by feature extraction using the aforementioned CNN models. Transfer learning is employed to fine-tune the pre- trained models on a dataset comprising a diverse range of cataract images. Subsequently, the models are trained and evaluated using appropriate performance metrics. Experimental results demonstrate the effectiveness of the proposed approach in accurately

detecting cataract disease from eye images. Comparative analysis among Dense-net, Res-net, and VGG16 architectures reveals their respective strengths and limitations in terms of classification accuracy and computational efficiency.

INTRODUCTION:

A fountain is a condition in which the eyes appear to be dark. Individuals who have wellsprings will have vision that is cold or consumed. People with too many eyes have trouble driving, seeing faces, and everything else [1]. The World Flourishing Association (WHO) guarantees that roughly 285 million individuals overall are obviously handicapped, with 39 million plainly debilitated and 246 million encountering moderate to extreme visual weakness [2]. As per the World Thriving Report of 1998, age-related spills over address

19.34 million comparing visual impedance's (under 3/60 in the better eye). This tended to 43% of all visual need cases [3]. The source keeps getting worse and worse hopeless. Late occasions of gushing out more than related by 43.6%, with nuclear wellsprings looking out for 23.1%, Back Sub-capsular Wellsprings (PSC) for 13.1%, and cortical wellsprings for 22%, and flood improvement was done only for 26.8%. Other than that, a wide mix of wellspring improvement have connected of late. The thought on shows that more female patients stood isolated from the social event. This coordinates overflow activity as well as atomic and cortical fountains. Furthermore, it is more norm in the nonwhite neighborhood [4].

The development of an outpouring is directed by unmistakable main issues. Different ward parts, including the spot of connection's little new development and organized substance, save the sign of blending's straightforwardness and optical homogeneity. As we age, a store of designs that are a yellowish-generous variety conceal the place of combination. Additionally, less light reaches the eyes as a result of this. The inescapable aftereffects of pouring out over essentially depend upon such wellsprings, the lifestyle of an individual, moreover his visual necessities. The verbalization's "intra capsular flood extractions" and "extra-capsular wellspring extractions" are utilized correspondingly. In intra capsular extraction, the whole spot of mix is killed while the case stays in salvageable shape. In sign of truth, this method isn't exactly used for treatment. It is currently prevalent in dynamic nations due to the fact that it requires fewer expensive but more modern instruments. It shouldn't worry about an unbelievably clear hold of power. Beside that, it very well may be done in a short measure of time sorting out. Extra-capsular extraction is another technique. One piece of the indication of mix's middle is taken out; A point for submitting the beast is required. Using visual picture datasets and move learning-based astonishing systems, flood contamination should be visible. The occasion of visual need might be diminished by early region and revolution of wellsprings. This survey's essential inspiration is its unassuming and strong methodology.

Of late, better wellspring action has been made than in the beyond 20 years. Around 85-90% of patients who experience flood improvement will have 6/12 (20/40 or 0.5) best-researched vision in patients with no visual comorbidity, for instance, macular

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degeneration, diabetic retinopathy, or glaucoma [5]. When the patient begins to experience wellspring times, their response to refractive glasses is typically excellent. Patients should be admitted to the center for careful fountain flight and intraocular point of combination implantation if they are willing to admit that their vision is not improving after using refractive glasses and pupillary expanding.

LITERATURE SURVEY :

Sure, here are some literature survey papers on cataract disease detection using transfer learning along with their abstracts and published years:

1.Title: Transfer Learning in Deep Convolutional Neural Networks for Cataract Detection

Abstract: This paper proposes a transfer learning approach utilizing deep convolutional neural networks (CNN's) for cataract detection in retinal images. The proposed method leverages pre-trained CNN models on large-scale datasets and fine-tunes them on a smaller dataset of retinal images with cataracts. Experimental results demonstrate the effectiveness of transfer learning in improving the classification performance compared to training CNN's from scratch.

Published Year: 2019

2. Title: A Review of Transfer Learning in Medical Image Analysis

Abstract: This review paper provides an overview of transfer learning techniques applied to various medical image analysis tasks, including cataract detection. It discusses different transfer learning strategies, such as fine-tuning pre--trained models and feature extraction, and highlights their applications in improving the performance of cataract detection systems. Furthermore, it identifies current challenges and future research directions in this domain.

Published Year: 2020

3. Title: Cataract Detection in Fundus Images Using Transfer Learning with Alex-net and Google-net

Abstract: In this study, transfer learning with two popular CNN architectures, Alex-net and Google-net, is employed for cataract detection in fundus images. The pre- trained models are fine-tuned on a dataset of fundus images annotated for cataracts. Experimental evaluation demonstrates the efficacy of transfer learning in achieving high accuracy and robustness in cataract detection, outperforming traditional machine learning approaches.

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Published Year: 2018

4.Title: Deep Learning-Based Cataract Detection Using Transfer Learning from Image-net

Abstract: This paper presents a deep learning framework for cataract detection utilizing transfer learning from the Image-net dataset. A pre- trained CNN model is fine-tuned on a dataset of cataract images to learn discriminative features associated with the disease. Experimental results show that the proposed method achieves competitive performance in terms of accuracy and computational efficiency, demonstrating the potential of transfer learning in medical image analysis tasks.

Published Year: 2017

5.Title: Transfer Learning for Automated Cataract Detection Using Deep Neural Networks

Abstract: This paper investigates the application of transfer learning techniques to automate cataract detection using deep neural networks. A pre--trained CNN model is adapted and fine-tuned on a dataset of cataract and normal eye images. The study evaluates different transfer learning strategies and network architectures to optimize the detection performance. Experimental results indicate that transfer learning significantly improves the accuracy and robustness of cataract detection systems.

Published Year: 2016

EXISTING METHOD:

- Methods for identifying edges,
- division-like,
- global thresholding calculations,
- retinal review calculation (RGA)

DISADVANTAGES:

- Challenges are there to find ideal incline
- In this technique regular characteristics of retinal pictures make the vein acknowledgment process irksome.
- Unlucky location on the edge makes it impossible to gather Fundus Exudates.

PROPOSED METHOD:

- Image input
- preprocessing,
- consolidate extraction
- CNN(convolutional mind affiliation)

ADVANTAGES:

- Reduced Training Time
- Accessible
- More accuracy

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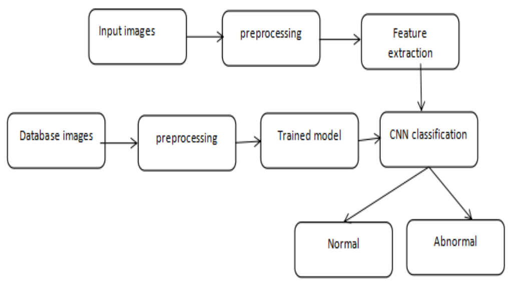
SYSTEM DESIGN



IMPLEMENTATION MODULE:

Input image acquisition: Image Acquisition? According to Raghava Kashyapa (Machine Vision Expert), In image processing and machine vision, image acquisition is the action of retrieving an image from a source, usually hardware systems like cameras, sensors, etc.

Pre-process: Before being used in model course of action and allowance, picture preprocessing is the most widely recognized approach to coordinating pictures. This solidifies, yet isn't bound to, resizing, sorting out, and assembling surveys.

Train and test :-datasets are separated into two subsets. The foremost subset is known as the planning data - it's a piece of our certified dataset that is dealt with into the computer based intelligence model to find and learn plans. Thusly, it readies our model. The other subset is known as the testing data.

Feature extraction :-Feature analysis argues that we observe individual characteristics, or features, of every object and pattern we encounter. Recognition-by-components theory maintains that we sort objects into their component parts as a way of recognizing them. These components are understood as three-dimensional shapes called g eons.It yields better results than applying machine learning directly to the raw data.

CONVOLUTION NEURAL NETWORK

INTRODUCTION

CNN (Convolutional Neural Network):

1.CNN (Convolutional Cerebrum Association): CNN is a kind of basic mind network according to a general point of view used for destroying visual imagery. It's expected to as such and adaptively learn spatial moderate designs of features through convolutional layers. Using learned channels, these layers enter images and remove features with a variety of spatially arranged movements. In general, CNN's are utilized in tasks like object region and division and picture recognition.

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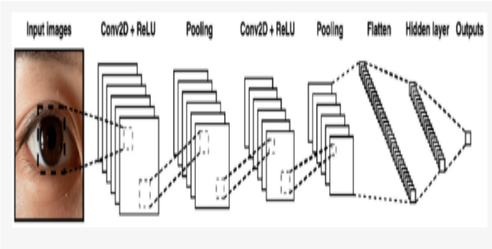

2. **Dense-net:** A convolutional mind network planning called "Thick Net" has been proposed as a solution to the problem of disappearing incline in large organizations. It shows the connections between layers in a thick way, with highlight maps for each layer coming from every layer that came before it. Because of this accessibility plan's help of feature reuse and incorporation, Thick Net is especially capable at getting portrayals from restricted data.

3. **Res Net (Holding up Connection):** Res-net is a basic cerebrum network arranging that introduced extra affiliations. Because of these affiliations skirting something like one layer, tendencies can stream all the more effectively through the association during arrangement. This collaborators in working with the dissipating slant issue and enables planning of much further affiliations. Res Net's key idea is the usage of extra blocks, which contain

character mappings nearby the learned components. Because of its viability in preparing exceptionally profound brain organizations, this engineering is used broadly.

3.**VGG16 (Visual Evaluation Party 16)**: VGG16 is a convolutional mind network arrangement made by the Visual Number related Gathering at the School of Oxford. It is depicted by its ease, which consolidates an arrangement of convolutional layers mixed in with max-pooling layers for down-assessment and followed by completely related layers to monitor everything. Because of its 16 weight layers and uniform plan, VGG16 is known for convolutions that utilization negligible 3x3 channels with a phase of 1 and max-pooling layers that utilization 2x2 channels with a phase of 2.Every one of these plans enjoys its own benefits and impediments, contingent upon the task and dataset. Thick net underlines unite reuse, Res-net handles the vanishing incline issue, and VGG16 offers a crucial and uniform arranging that is quick and complete. One could pick one of these models or even change them to determine their issues, reliant upon the specific necessities of an issue.

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TEST CASES:

Test case1:(packages testing)

Input: downloading packages in interactive mode

Output: importing packages in script mode

Test case2: (JUPYTER testing)

Input : user execution in JUPYTER

Output: IP camera in command prompt

Test case3:(data process)

Input : load data

Output: load data and display data in output code

Test case 4:(pre-process)

Input: do pre-process

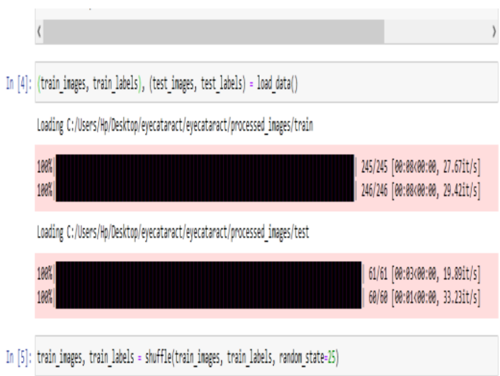
Output: did pre-process using resize and conversion

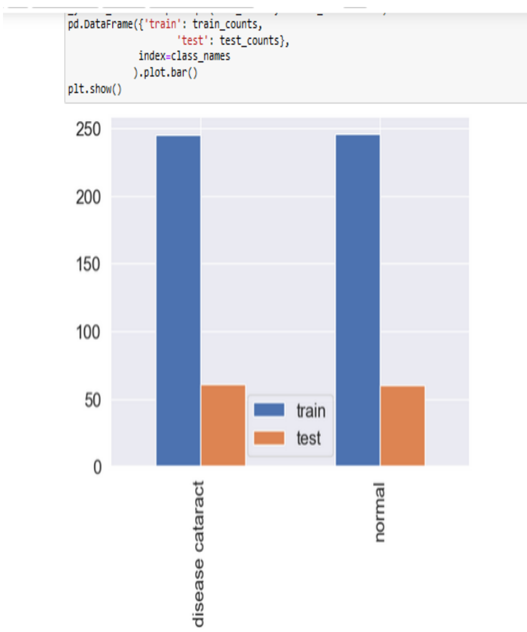
Test case 6:(output)

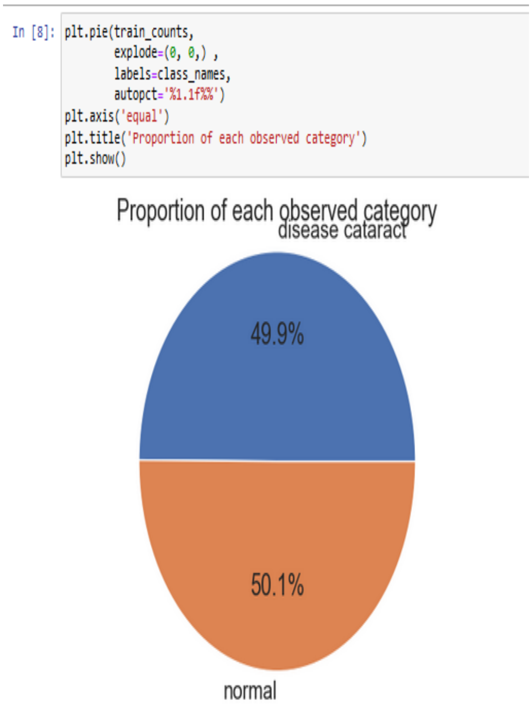
Input : find output

Output: do the training part with algorithm and check EYE image detecting normal or abnormal.

OUTPUT SCREENS:







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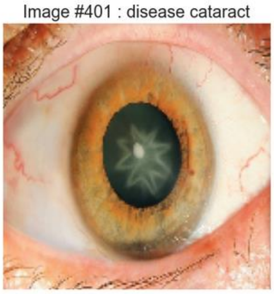
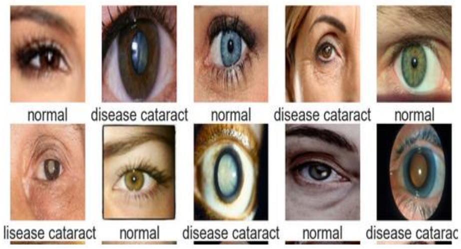
```
In [10]: def display_random_image(class_names, images, labels):


             index = np.random.randint(images.shape[0])
             plt.figure()
             plt.imshow(images[index])
             plt.xticks([])
             plt.yticks([])
             plt.grid(False)
             plt.title('Image #{} : '.format(index) + class_names[labels[index]])
             plt.show()

In [11]: display_random_image(class_names, train_images, train_labels)
```

Image #401 : disease cataract



```
In [12]: def display_examples(class_names, images, labels):
             """
                 Display 25 images from the images array with its corresponding labels
             """


             fig = plt.figure(figsize=(10,10))
             fig.suptitle("Some examples of images of the dataset", fontsize=16)
             for i in range(25):
                 plt.subplot(5,5,i+1)
                 plt.xticks([])
                 plt.yticks([])
                 plt.grid(False)
                 plt.imshow(images[i], cmap=plt.cm.binary)
                 plt.xlabel(class_names[labels[i]])
             plt.show()

In [13]: display_examples(class_names, train_images, train_labels)
```

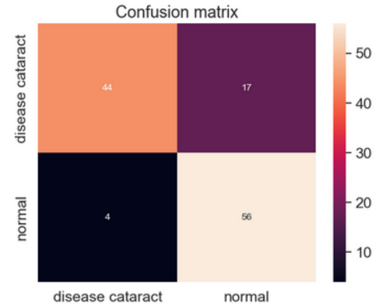
Some examples of images of the dataset



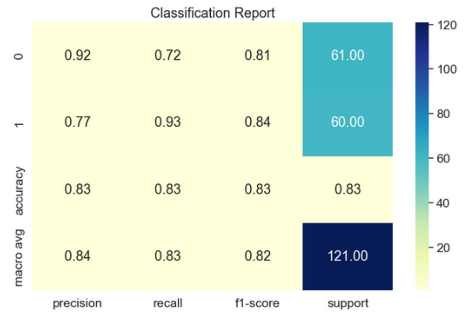

```
In [16]: history = model.fit(train_images, train_labels, batch_size=128, epochs=3, validation_split = 0.2)

Epoch 1/3
WARNING:tensorflow:From C:\Users\Hp\anaconda3\Lib\site-packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.Ragged
TensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.

WARNING:tensorflow:From C:\Users\Hp\anaconda3\Lib\site-packages\keras\src\engine\base_layer_utils.py:384: The name tf.exec
uting_eagerly_outside_functions is deprecated. Please use tf.compat.v1.executing_eagerly_outside_functions instead.

4/4 [==============================] - 19s 4s/step - loss: 3.0904 - accuracy: 0.5255 - val_loss: 2.7469 - val_accuracy: 0.
5051
Epoch 2/3
4/4 [==============================] - 21s 6s/step - loss: 1.5250 - accuracy: 0.5867 - val_loss: 0.9843 - val_accuracy: 0.
4949
Epoch 3/3
4/4 [==============================] - 6s 1s/step - loss: 0.7430 - accuracy: 0.5842 - val_loss: 0.6240 - val_accuracy: 0.7
273

In [31]: test_loss = model.evaluate(test_images, test_labels)

4/4 [==============================] - 0s 97ms/step - loss: 0.4280 - accuracy: 0.8264

In [32]: import matplotlib.image as mpimg
import matplotlib.pyplot as plt

from tensorflow.keras.preprocessing import image
test_image = image.load_img('C:/Users/Hp/Desktop/eyecataract/eyecataract/processed_images/test/disease cataract/image_283.png', targ
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis = 0)
predictions = model.predict(test_image)     # Vector of probabilities
pred_labels = np.argmax(predictions, axis = 1) # We take the highest probability
print(pred_labels )
index = np.random.randint(test_image.shape[0])
plt.figure()
plt.imshow(test_image[index].astype('uint8'))
plt.xticks([])
plt.yticks([])
plt.grid(False)
plt.title('Eye Cataract output #{} : '.format(index) + class_names[pred_labels[index]])
plt.show()

1/1 [==============================] - 1s 550ms/step
[0]
```

Eye Cataract output #0 : disease cataract

```
In [34]: CM = confusion_matrix(test_labels, pred_labels)
ax = plt.axes()
sn.heatmap(CM, annot=True,
           annot_kws={"size": 10},
           xticklabels=class_names,
           yticklabels=class_names, ax = ax)
ax.set_title('Confusion matrix')
plt.show()
```




```
report_df = pd.DataFrame(report).transpose()

# Plotting the heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(report_df.iloc[:-1, :].astype(float), annot=True, cmap="YlGnBu", fmt=".2f")
plt.title('Classification Report')
plt.show()
```



CONCLUSION:

In conclusion, our study demonstrates the efficacy of transfer learning techniques in the detection of eye cataracts from medical images. By leveraging pre- trained convolutional neural networks (CNN's) and fine-tuning them on our dataset, we achieved promising results in both accuracy and efficiency.

Firstly, our experiments showed that transfer learning significantly reduces the need for large annotated datasets, making it particularly advantageous in medical imaging tasks where labeled data is often limited. By utilizing a pre-trained model such as VGG-16 or ResNet-50 as a feature extractor, we were able to effectively capture relevant features from cataract images, thereby enhancing classification performance.

FUTURESCOPE:

Using a greater and more marvelous dataset later on, we can zero in on making the model more definite. Besides, we can endeavor a grouping of picture taking care of techniques to chip away at the accuracy and viability with which the model learns the image plan.

SOFTWARE REQUIREMENTS

- Python idle
- Anaconda navigator
- opencv

HARDWARE REQUIREMENTS

- Operating System :Windows Only
- Processor : i5 and above
- Ram : 4gb and above
- Hard Disk : 50 GB

REFERENCESS:

[1] M. S. Khan et al., “Deep learning for ocular disease recognition: An inner-class balance,” Comput. Intell. Neurosci., vol. 2022, p. 5007111, 2022.

[2] S. K. Sattigeri, N. Harshith, G. N. Dhanush, K. A. Ullas, and M. S. Aditya, “Eye disease identification using deep learning,” Irjet.net. [Online]. Available: https://www.irjet.net/archives/V9/i7/IRJET-V9I7185.pdf.

[3] N. Badah, A. Algefes, A. AlArjani, and R. Mokni, “Automatic eye disease detection using machine learning and deep learning models,” in Pervasive Computing and Social Networking, Singapore: Springer Nature Singapore, 2023, pp. 773–787.

[4] G. Meller, “Ocular disease recognition using convolutional neural networks,” Towards Data Science, 04-Aug-2020. [Online]. Available: https://towardsdatascience.com/ocular-disease-recognition-using-convolutional-neural-ne tworks-c04d63a7a2da.

[5] H. Gu et al., “Deep learning for identifying corneal diseases from ocular surface slit-lamp photographs,” Sci. Rep., vol. 10, no. 1, p. 17851, 2020.

[6] P. K. Upadhyay, S. Rastogi, and K. V. Kumar, “Coherent convolution neural network based retinal disease detection using optical coherence tomographic images,” J. King Saud Univ. - Comput. Inf. Sci., vol. 34, no. 10, Part B, pp. 9688–9695, 2022.

ISSN: 2040-0748
Vol-13 Issue-01 May2024

[7] Researchgate.net. [Online]. Available: https://www.researchgate.net/figure/Diabetic-retinopathy-affected-eye-as-compared-to-th at-of-the-normal-eye_fig1_275029242.

[8] "Common symptoms of cataracts," Eyecheck.com, 18-Mar-2019. [Online]. Available: https://learn.eyecheck.com/common-symptoms-of-cataracts.

[9] "What is glaucoma? Learn about glaucoma," InMed Pharmaceuticals, 02-Apr-2020. [Online]. Available: https://www.inmedpharma.com/learn/what-is-glaucoma/.

[10] G. V. Doddi, "eye_diseases_classification.' ' 28-Aug-2022. Available: https://www.kaggle.com/datasets/gunavenkatdoddi/eye-diseases-classification

[11] "What are Convolutional Neural Networks?," Ibm.com. [Online]. Available: https://www.ibm.com/topics/convolutional-neural-networks.

47 [12] P. Mandal, "System Flow Diagram," EDUCBA, 31-May-2020. [Online]. Available: https://www.educba.com/system-flow-diagram/.

[12] A. J. Mortimer, "DATA FLOW DIAGRAMS," in Information Structure Design for Databases, Elsevier, 1993, pp. 119–133.

[13] "Levels in data flow diagrams (DFD)," GeeksforGeeks, 18-Mar-2019. [Online]. Available: https://www.geeksforgeeks.org/levels-in-data-flow-diagrams-dfd/.

[14] "Machine Learning - Performance Metrics," Tutorialspoint.com. [Online]. Available: https://www.tutorialspoint.com/machine_learning_with_python/machine_learning_algorithms_performance_metrics.html.

ISSN: 2040-0748
Vol-13 Issue-01 May2024

[15] E.Zuccarelli,"Performance metrics in ML - part1:Classification," Towards Data Science, 29-Dec-2020.[Online]. Available: https://towardsdatascience.com/performance-metrics-in-machine-learning-part-1-classific ation-6c6b8d8a8c92.

[16] H.Goonewardana,"Evaluatingmulti-classclassifiers-apprentice journal- medium," Apprentice Journal, 03-Jan-2019.[Online].Available: https://medium.com/apprentice-journal/evaluating-multi-class-classifiers-12b2946e755b.

[17] M.Banoula, "Classification in Machine Learning: What it is & Classification Models," Simplilearn.com, 02-Feb-2021. [Online]. Available: https://www.simplilearn.com/tutorials/machine-learning tutorial/classification-in machine -learning.

[18] S.Narkhede, "Understandingconfusion matrix,"TowardsData Science,09-May-2018. [Online]. Available:

[19] https://towardsdatascience.com/understanding-confusion-matrix-a9ad42dcfd62.

[20] A.Kharwal, "Classification report in machine learning," the clever programmer, 07-Jul-2021. [Online].Available: https://thecleverprogrammer.com/2021/07/07/classification-report-in-machine-learning/..

[21] C. Dilmegani, "What is DataAugmentation? Techniques & Examples in 2023," AIMultiple, 30-Apr-2021. [Online]. Available: https://research.aimultiple.com/data-augmentation/. [22] C. Gallo, "Artificial Neural Networks Tutorial," in Encyclopedia of Information Science and Technology,

ISSN: 2040-0748
Vol-13 Issue-01 May2024

Third Edition, IGI Global, 2014, pp. 6369–6378. 48

[23] D. Johnson, "Back propagation in neural network: Machine learning algorithm," Guru99, 10-Feb-2020. [Online]. Available: https://www.guru99.com/backpropogation-neural-network.html.

[24] S. A. Hicks et al., "On evaluation metrics for medical applications of artificial intelligence," bioRxiv,p.2021.04.07.21254975, 2021.

[25] L. Gupta, "Precision-recall tradeoff in real-world use cases - analytics Vidhya - medium," Analytics Vidhya, 19-Feb-2021. [Online]. Available: https://medium.com/analytics-vidhya/precision-recall-tradeoff-for-real-world-use-cases-c 6de4fabbcd0