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SMALL MEDICAL IMAGE IDENTIFICATION USING YOLOV8 ALGORITHM

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Abstract - *Brain tumor disease refers to any Brain irregularity causing its damage. There are several kinds of Brain ailments. Benign growths are rarely life threatening and can be removed by specialists. Brain malignant tumor is one of the world's leading causes of cancer death. Identifying malignant growth tissue is a troublesome and tedious task. This research aims to optimize the latest YOLOv8 model to improve its detection of small Images and compare it with another different version of YOLO models. To achieve this goal, we used the classical deep learning algorithm YOLOv8 as a benchmark and made several improvements and optimizations. There is significantly less information and statistical analysis presented related to cholangiocarcinoma and hepatoblastoma. This research focuses on the image analysis of these two types of cancer. The framework's performance is evaluated using 2871 images, and a dual hybrid model is used to accomplish superb exactness. The first is the SID (Small Image Detection) dataset [11], a collection of images specifically curated and annotated for small Image detection tasks. Small Image detection aims to identify and highlight an image's most visually distinctive Images or regions. The second one is the bacterial colony dataset [12], which is a collection of images specifically focused on bacterial colonies grown in a laboratory setting. The aftereffects of both neural networks are sent into the result prioritize that decides the most ideal choice for image arrangement. The technique entails extracting characteristics from the start and combining them with residual and pre-trained weights. This deep learning YOLOv8 system demonstrates the concept of illuminating elements of a pre-trained deep neural network's decision-making process by an examination of inner layers and the description of attributes that contribute to predictions.*

Key Words: **Brain Tumor Detection, YOLOv8 Algorithm Deep Learning, Discrete Wavelet Transform (DWT).**

1.INTRODUCTION

Computerized image handling uses processing to deal with advanced images by using an advanced PC. Many issues emerge in the current framework, for example, giving countless faulty rates, over-segmenting tumor regions, high time complexity, low exactness, and it is a troublesome to deal with constructions of high inconsistency with a lot of disturbances that happen during division.

1.1 Background

Image detection is an essential task in the computer vision field, which is widely used in real-time video analysis, automatic driving, and intelligent security. Before 2014, traditional target detection algorithms required extracting features manually, which was time-consuming and unstable. The SOTA algorithm DPM [1] detector at that time, although inference speed was faster than others and could adapt to slight deformation, could not adjust to large-scale rotation and showed low robust ability. The dynamic shape method and deep learning YOLOv8 calculations involve recognizing inappropriate sources of info and furnish definite results with an identical viable allowance, such as recognizing a wide range of Brain problems in solitary handling. The topology of medical imaging methodologies is presented in Fig. 1. Hepatic carcinoma (HCC) is the subsequent reason for malignant growth deaths around the world, and it is the most normal essential cause of hepatocellular disease in individuals. Unlike other diseases, the incidence of HCC is rising [2]. YOLOv8 are useful in detecting and analyzing quickly and dependably the HCC in individuals, bringing about better results [3]. As the quality and accessibility of cross-sectional imaging have expanded, the requirement for intrusive demonstrative biopsies has diminished, driving imaging to a more fundamental position with an evident status, especially in essential Brain malignancies [4]. The Brain is likely the most often examined organ, and metastases are processes that aid in the detection, diagnosis, and management of hepatic disorders.

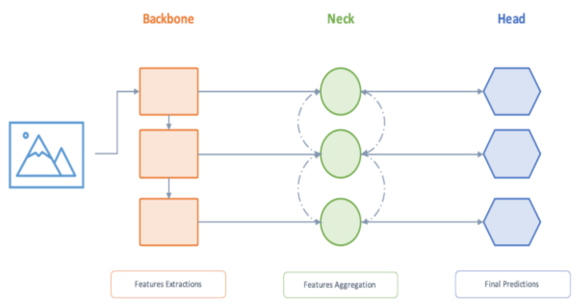

Fig -1: The architecture of YOLO consists of a backbone, neck, and head [11].

1.2 Motivation

AI calculations have increased radiological proficiency and have the potential to overcome any challenges in the radiological classification of various infections. To recognize images, fully YOLOv8 do not require recognizable confirmation of explicit radiological qualities, and, unlike other AI methods, they may even disclose features that do not exist in radiological practice [14]. Velocity-bounded Boolean particle swarm optimization (PSO) is used to choose better features from brain malignant development data. When implemented in a hepatic CAD framework, the proposed technique selects the best characteristics utilised to classify hepatoma and cholangiocarcinoma as life threatening and hemangioma and focal nodular hyperplasia (FNH) as innocuous. YOLOv8 has some difficulties in dealing with small and dense targets and is prone to the problems of missed detection and overlapped detection, especially when the size of the Image is smaller than 8*8. YOLOv8 uses a predefined detection head, which is insufficient to detect the details of small targets, while it is easy to produce overlapping detection frames for dense targets [15].

1.3 Objectives of the paper

1. To detect disease from the medical images like MRI using the YOLOv8 algorithm

2. To evaluate of the accuracy, precision, recall and specificity of the model.

3. To compare of the results from the existing modeling and proving our model provides best accuracy, precision, recall and specificity compare to other models.

2. LITERATURE SURVEY

Steven Smiley et.al [1] This reserach is about the Centers for Disease Control and Prevention (CDC). Heart disease is the primary cause of death in the United States for most racial and ethnic groups, as well as for both men and women. It costs the nation billions of dollars and takes the lives of more than one person every minute, as well as over 500,000 Americans annually. Therefore, the purpose of this article is to investigate a wide range of potential supervised Machine Learning (ML) algorithms for heart illness diagnostic modeling.

Syed Nawaz Pasha1 et.al [2] This essay focuses on cardiovascular disease, also known as coronary sickness, which is one of the very serious and severe illnesses in both India and world wide. According to estimates, cardiac illnesses account for 28.1% of fatalities. In 2016, it was the primary cause of a considerable number of deaths, with over 17.6 million deaths attributed to it. For these diseases to be properly diagnosed and treated in a timely manner, a precise, reliable prediction system is necessary. Numerous academics do extensive research utilizing a various types of machine learning algorithms to anticipate heart illness using various datasets that contain numerous factors that lead to a heart attack.

Mohd Ashraf et.al [3] This study focuses on heart disease, which is the primary concern for medical professionals. It has been noticed that medical staff need assistance in determining a patient's risk of experiencing a heart attack. Recently, a great deal of work has gone into creating an automated help system that can determine an individual's risk of suffering a heart attack. Scientists discovered they may make a contribution to certain significant interdisciplinary subjects, including medical science, with the emergence of computer science. The potential of any particular algorithm is not adequately represented by the single data set that was used to evaluate machine learning techniques. They also exhibit a few of the more significant anomalies, such accuracy and manual data set pre-processing. In this research, we propose to develop an automated system for heart attack prediction using Deep Neural Network approaches.

Awais Mehmood1 et.al [4] This study focuses on cardiac problems, which are currently the world's biggest cause of death. This is a severe problem in growing economies in Asia and Africa. In addition to helping people avoid heart attacks, early identification of heart disease allows medical personnel to determine the primary risk factors for heart attacks and take preventative action before a patient has one. In this study, we introduce a new approach called Cardio Help that estimates the probability that a patient has cardiovascular disease using convolutional neural networks (CNNs), a deep learning technique. The suggested method models temporal data by utilizing CNN to predict HF early on. By generating the dataset on heart disease and comparing the results with the most recent approaches available, we were able to acquire good results. Experimental results show that the proposed technique outperforms the existing methods in terms of performance assessment metrics. The achieved accuracy of the proposed approach is 97%.

P Kalpana1 et.al [6] This paper focus on the symptoms of heart disease in the first stage and stop it, given the increased increase in stroke rate at the tender level. It's funny for the average man to show the more expensive electrocardiogram questions every day. Because of this, there should be a favorable consensus in the area at a consistent time when the risk of heart disease is predicted. For this reason, we want to create an Assistant in the nursing framework that can predict the risk of heart disease due to key indicators such as age, gender, and heart rate. Neural codes for learning neural codes are well tested to be the most reliable and robust, and as a result, included in the predicted correlation.

Harshit Jindal1 et.al [7] This paper emphasis on heart diseases are increasing at a rapid rate and it's very

Important and concerning to predict any such diseases beforehand. This diagnosis is a difficult task i.e. it should be performed precisely and efficiently. The research paper mainly focuses on which patient is more likely to have a heart disease depending on various medical attributes. We prepared a heart disease prediction system to predict whether the patient is likely to be diagnosed with a heart disease or not using the medical history of the patient. We used various algorithms of machine learning such as logistic regression and KNN to predict and classify the patient with heart disease.

3. PROPOSED SYSTEM ARCHITECTURE

3.1 Flow of the system

A database of 2871 images is collected, and then for feature extraction purpose, a wavelet transform is used (flow of the classifier is shown in Fig. 3). Then, to reduce the dimensionality of the features, PCA is used. The after statistical parameters are being extracted to obtain a result from the classifier.

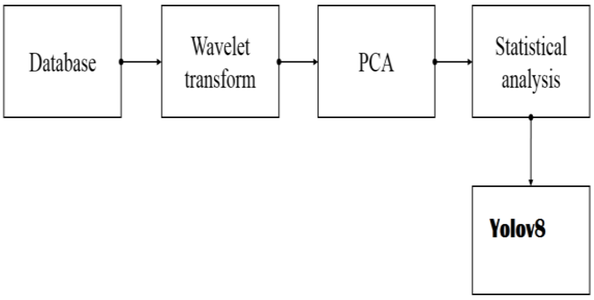

Fig.2: Flow of the system.

3.2 Proposed architecture model

A dual hybrid model is utilized to achieve great precision. The aftereffects of both neural networks are then conveyed to the result prioritizer who settles on an official choice of image description. In the event that the aftereffects of both neural networks are comparable (which is, for the most part, the case), then, at that point, the same outcome turns into the end product. The diagrammatic representation of the proposed system architecture is presented in Fig. 4.

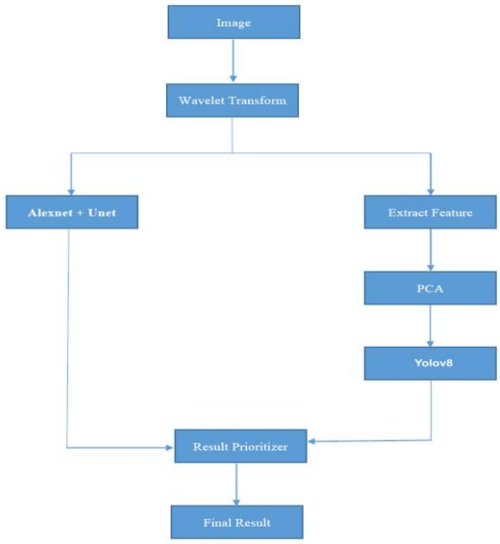

Fig.3: Proposed architecture model.

Alex Net + U-Net: Before the picture is fed into a hybrid (AlexNet and U-Net) neural network model, it first undergoes a wavelet treatment. We therefore obtain a categorization outcome.

3.3 YOLOV8

3.3.1 Models Architecture

The backbone and head of a convolutional neural network are the two fundamental components of the YOLOv8 architecture, which is an improvement over earlier iterations of the YOLO algorithm [8]. A revised Currently, CS architecture that consists of thirty-five convolutional layers and uses cross-stage fractional connections to enhance the transfer of data between layers serves as the foundation of YOLOv8. The bounding boxes, item evaluations, and probabilities of classes of recognized Images are anticipated by the YOLOv8 head, which is made up of a number of convolutional layers followed by fully connected layers. A noteworthy aspect of YOLOv8 is the inclusion of an apparatus for self-attention [9] in the network's head. This feature enables the model to concentrate on various areas of the imagery and change the value of elements according to relevance. Another noteworthy aspect of YOLOv8 is its capacity to recognize Images on many scales, which is accomplished via a characteristic hierarchy network [10]. The model can reliably recognize things of various sizes inside an image because to the network's numerous layers that detects Images at various scales. Figure 4 displays a typical YOLOv8 model structure.

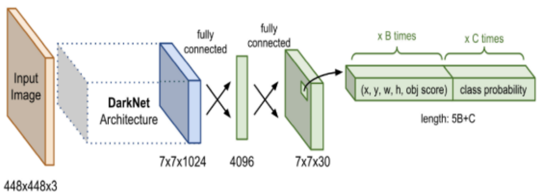

Fig 4: YOLO Network Architecture [12]

3.3.2. Head

To address the limitations of traditional methods, regression-based approaches have emerged as a research focus in the field of three-dimensional human pose estimation. These methods leverage deep learning techniques to learn the mapping relationship from images to pose and shape, enabling direct regression of human pose and shape. This method uses deep neural networks and a large amount of training data to get estimation results that are more accurate. In YOLOv8, the "head" part refers to the top-level hierarchical structure of the neural network model, which is liable for processing the feature map after feature extraction from the basic level [11]. Specifically, the "head" part of YOLOv8 mainly includes three key components: detection layers, up sample layers, and route layers. The detection layers are liable for converting input feature maps into detection bounding boxes. Up sample layers are used to increase the resolution of the feature map. The up-sampling layer is mainly used to increase the model's perception of small-sized Images. The route layer is used to connect feature maps of different levels. It can connect the previous layer's feature map with the earlier layer's feature map to obtain feature maps with different scale feature information [12]. This multi-scale feature fusion helps the model to detect Images of different sizes and types.

3.3.3. Deficiency and optimizer

In standard Image detection tasks, the problem of missing detection or poor detection effect often occurs when there are small Images in the data set. The reason is stated as follows: The YOLOv8 model has detection heads by default, which can perform multi-scale detection of targets. Among them, P3/8 corresponds to a detection feature map size of 80*80, which is utilized for recognizing items larger than 8*8; P4/16 relates to a detection feature map size of 40*40, which is applied to recognize items larger than 16*16; and P5/32 corresponds to a recognition characteristics map size of 20*20, which is used to identify items larger than 32*32, as illustrated below:

3.4 Pseudo Code of Algorithm YOLOv8

Updated head: detecting small Images

1 [-1, 1, nn.Unsample, [None, 2, 'nearest']]

2 [[-1, 6], 1, Concat, [1]] # cat backbone P4

3 [-1, 3, C2f, [512]] # 12

5 [-1, 1, nn.Upsample, [None, 2, 'nearest']]

6 [[-1, 4], 1, Concat, [1]] # cat backbone P3

7 [-1, 3, C2f, [256]] # 15 (P3/8-small)

9 [-1, 1, Conv, [256, 3, 2]]

10 [[-1, 12]. 1, Concat, [1]] # cat head P4

11 [-1, 3, C2f, [512]] # 18 (P4/16-medium)

13 [-1, 1, Conv, [512, 3, 2]]

14 [[-1, 9], 1, Concat, [1]] # cat head P5

15 [-1, 3, C2f, [1024]] # 21 (P5/32-large)

16 [[15, 18, 21], 1, Detect, [nc]] # Detect(P3, P4, P5)

Then it emerges instinctively that there may be a problem of poor capability for detecting tiny Images whose sizes are smaller than a particular scale or one of the dimensions (width and height) is not large enough. This study introduces a tiny Image detection layer (160*160 detection feature map for identifying targets above 4*4, for example) to enhance the detection performance of small targets. To achieve this improvement, we maintain the original results in the Backbone part but adjust the model structure of the head part, see below:

Optimizer： New detection head

1 [-1, 1, nn.Upsample, [None, 2, 'nearest']]

2 [[-1, 2], 1, Concat, [1]] # cat backbone P3

3 [-1, 3, C2f, [128]] # 18 (P2/4-xsmall)

3.5 Dataset

Generally speaking, we totally apply two different datasets to test the performance of our network. The first is the SOD (Small Image Detection) dataset [11], a collection of images specifically curated and annotated for small Image detection tasks. Small Image detection aims to identify and highlight an image's most visually distinctive Images or regions. The images in such dataset are scaled to 640*640 and the average size of Images is about 25*25. We train this dataset with multiple models with epochs = 30, image size = 640, and batch size = 3. The second one is the bacterial colony dataset [12], which is a collection of images specifically focused on bacterial colonies grown in a laboratory setting. It is commonly used in microbiology and bioinformatics research to study bacterial growth patterns, analyses colony characteristics, and develop automated colony recognition and classification algorithms. The image in such a dataset is scaled to 1280*1295. Various large-size bacteria (about 10*10) and tiny-size bacteria (about 2*2) constitute each image. We train this dataset with multiple models with epochs = 15, image size = 640, and batch size = 10.

4. RESULT AND DISCUSSION

4.1 Performance

The recall rate, precision, and mAP are three essential criteria in medical Image detection. Therefore, this paper emphasizes the importance of comparing these metrics to evaluate the pursuance of Image detection models. The recall rate refers to the fraction of actual Images in an image that the model correctly detected. Precision relates to the fraction of detected Images correctly identified and not falsely detected. mAP (mean average precision at 50% Intersection Over Union) is a way to summarize precision and recall over multiple classes in Image detection tasks, providing a holistic view of a model's performance. The P-R curve of our model is in Figure 5.

4.2 Comparison with YOLOv8n network

The YOLOv8n network underwent a series of optimizations, and the subsequent results have been encouraging. Upon comparing the optimized network with the original YOLOv8n model, its performance metrics showed a clear enhancement. Visual comparison with YOLOv8 is in Figure 5. A comparison of widely used metrics. Specifically, when the improved model was trained on the SOD dataset, a marked improvement in both prediction accuracy and training velocity was observed, most notably during the initial 5 epochs. The optimized network's final precision is 92.4%, a 4% improvement over the original network. The best recall rate increased by 4% to 73.4% after optimizing the YOLOv8n network. After adding the detection head, the mAP50 increased from 74.2% to 78.4%. This means that the optimized network can predict the Image's location more precisely. It is worth emphasizing that these enhancements were not just confined to the accuracy metrics, they also appeared in the training speed. In the initial five epochs, the mAP50 of the optimized network is about 10% higher than the original network. Concurrently, precision and recall rates surged quicker in the optimized network, further accentuating its advantages over the original version. Due to the computational power limitations and the number of training epochs, the enhancements to the network are not significant. The authentic images of the SOD dataset are 1280*1295 pixels. However, to reduce the amount of calculation, the images were compressed to 640*640 pixels. Therefore, the improvement was not noticeable. Besides, the training loss and the validation loss didn't show any improvement. The optimized network seems to have some deficiencies when it is applied to different datasets. The optimized network does not show improvement when trained on the bacterial colony dataset. This needs further exploration because of the small quantity of datasets and training
time.

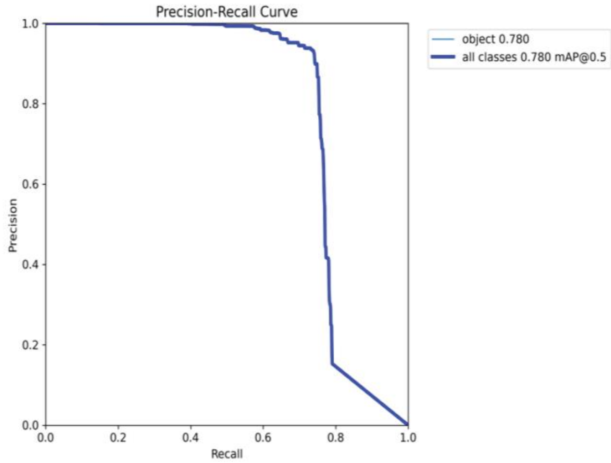

Fig 5: Precision-Recall curve.

4.3 Comparison with other detection networks

Compared with the former version of the YOLO network, there are more significant improvements. After training 15 epochs on SOD dataset, the recall rate of the YOLOv5n is 65.5% and the optimized YOLOv8n achieved the rate of 72.4%, which is more obvious. The improvements in precision and mAP are also higher than the previous comparison. This is partly due to the YOLOv8n's performance itself. The original YOLOv8n network's training speed is almost the same as that of YOLOv5n and YOLOv3. Therefore, it proves that the training speed of the network had indeed increased, in the early training state. However, when it comes to the network loss, the optimized YOLOv8n network had even higher losses than the former version of the YOLO model.

5. CONCLUSION

To improve the pursuance of YOLOv8, this paper adds a detection head to the head of the model while keeping the structure of the backbone. As a result, the modified model can find small Images as small as 4*4 pixels. Compared to the original YOLOv8 model, our model shows a 4.2% higher precision rate and 4.0% higher recall rate in the task of detecting bacterial colonies and a rise of 9.2% with regard to mAP. In fact, the model can detect almost every colony visually, which means the model achieves our primary goal, namely counting anything. The experiment proved that adding a specified detection head can improve the ability of YOLOv8 to detect small Images. However, if this work adds too many detection heads, it's likely to slow down the training and inference process, which is an underlying drawback of our method. There are a few types of Brain malignant growths. The malignant growths of cholangiocarcinoma and hepatoblastoma are considered in this study. The framework's performance is evaluated utilizing 2871 images. A dual hybrid model is used to accomplish incredible precision. The results of both neural networks are sent to the result prioritizer, which settles on an ultimate conclusion on image order. Assuming that the aftereffects of both neural networks are comparative (which is by and large the case), then, at that point, the same outcome turns into the end product. Future work can focus on the segmentation of cancer tissues in 3D medical images.

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