A Project Report on

Intracranial Haemorrhage Detection

A Dissertation submitted to JNTU Hyderabad in partial fulfillment
of the academic requirements for the award of the degree.

Bachelor of Technology

In

Computer Science and Engineering

Submitted by

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EXPLORE TO INVENT

Department of Computer Science and Engineering

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KANDLAKOYA, MEDCHAL ROAD, HYDERABAD - 501401.

2020- 2024

CMR COLLEGE OF ENGINEERING & TECHNOLOGY

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the Major Project report entitled **"Intracranial Haemorrhage Detection"** being submitted by **Kothapalli Sai Puneeth** (**20H51A0596**), **Bathula Vishwani** (**20H51A05B3**), **Uyyala Anwesh Goud** **(20H51A05J8**) in partial fulfillment for the award of Bachelor of Technology in **Computer Science and Engineering** is a record of bonafide work carried out his/her under my guidance and supervision.

The results embodies in this project report have not been submitted to any other University or Institute for the award of any Degree.

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ACKNOWLEDGEMENT

With great pleasure we want to take this opportunity to express our heartfelt gratitude to all the people who helped in making this project a grand success.

We are grateful to **Mr. M. ShivaKumar,** Assistant Professor, Department of Computer Science and Engineering for his valuable technical suggestions and guidance during the execution of this project work.

We would like to thank**, Dr. Siva Skandha Sanagala,** Head of the Department of Computer Science and Engineering, CMR College of Engineering and Technology, who is the major driving forces to complete our project work successfully.

We are very grateful to **Dr. Ghanta Devadasu**, Dean-Academics, CMR College of Engineering and Technology, for his constant support and motivation in carrying out the project work successfully.

We are highly indebted to **Major Dr. V A Narayana,** Principal, CMR College of Engineering and Technology, for giving permission to carry out this project in a successful and fruitful way.

We would like to thank the **Teaching & Non- teaching** staff of Department of Dept Name for their co-operation

We express our sincere thanks to **Shri. Ch. Gopal Reddy**, Secretary& Correspondent, CMR Group of Institutions, and Shri Ch Abhinav Reddy, CEO, CMR Group of Institutions for their continuous care and support.

Finally, we extend thanks to our parents who stood behind us at different stages of this Project. We sincerely acknowledge and thank all those who gave support directly or indirectlyin completion of this project work.

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ABSTRACT

Brain Haemorrhage is the eruption of the brain arteries due to high blood pressure or blood clotting that could cause a traumatic injury or death. It is the medical emergency in which a doctor also need years of experience to immediately diagnose the region of the internal bleeding before starting the treatment. In this, the deep learning algorithms, Yolo model is proposed for the Brain Haemorrhage classification and detection. We use head CT scan images dataset to boost the accuracy rate and computational power of the deep learning models. The major aim of this study is to use the abstraction power of deep learning on a set of fewer images because in most crucial cases extensive datasets are not available on the spot. We propose the image augmentation and im-balancing the dataset methods with Yolo model to design a unique architecture and named as Brain Haemorrhage Classification based on Neural Network. The performance of the proposed approach will be analyzed in terms of accuracy, precision, sensitivity, specificity and F1-score.

CHAPTER 1

INTRODUCTION

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1.1 PROBLEM STATEMENT

Intracranial haemorrhage (ICH) poses a critical threat to patients, necessitating rapid detection for timely intervention and improved outcomes. However, manual analysis of medical imaging data for ICH detection is labor-intensive and prone to errors, leading to delays in diagnosis and treatment. To address this challenge, this project endeavors to develop an automated system utilizing the YOLO (You Only Look Once) algorithm. This advanced deep learning model will analyze CT or MRI scans to accurately identify and classify haemorrhages, offering a faster and more efficient alternative to manual interpretation. By harnessing the speed and effectiveness of YOLO, the system aims to enhance the early detection of ICH, enabling prompt medical intervention and potentially saving lives. This initiative aligns with the urgent need to leverage cutting-edge technology in healthcare, striving to advance diagnostic capabilities and ultimately improve patient care, especially in critical scenarios like intracranial haemorrhage detection.

1.2 RESEARCH OBJECTIVE

The primary objective of this research is to develop and evaluate an automated system for intracranial haemorrhage (ICH) detection utilizing the YOLO (You Only Look Once) algorithm. The specific research goals include:

Development of a robust deep learning model: Design and implementation of a YOLO- based algorithm tailored for ICH detection from CT or MRI scans, aiming for high accuracy and efficiency.

Dataset curation and preprocessing: Collection of a diverse dataset of medical imaging data containing labeled instances of ICH, followed by preprocessing steps such as noise reduction, standardization, and augmentation to enhance model training.

Model training and optimization: Training the YOLO algorithm on the curated dataset to effectively recognize and classify intracranial haemorrhages. Optimization of model architecture and parameters to achieve optimal performance.

Performance evaluation: Comprehensive assessment of the developed system's performance, including metrics such as accuracy, sensitivity, specificity, precision, and processing speed. Comparison with existing methods and validation against ground truth annotations.

Clinical relevance assessment: Evaluation of the algorithm's clinical utility and relevance in real-world healthcare settings, considering factors such as interpretability, integration with existing workflows, and potential impact on patient outcomes.

Exploration of deployment feasibility: Investigation into the feasibility of deploying the developed system in clinical practice, considering technical requirements, regulatory compliance, and usability considerations.

Iterative refinement and improvement: Iterative refinement of the algorithm based on feedback from performance evaluations and clinical stakeholders, aiming to continuously enhance its effectiveness and usability for ICH detection.

Overall, the research aims to advance the field of medical imaging by leveraging state-of-the-art deep learning techniques, specifically YOLO, to develop an automated solution for intracranial haemorrhage detection. By addressing key challenges in algorithm development, dataset preparation, performance evaluation, and clinical translation, the research seeks to contribute towards improving early diagnosis and treatment outcomes for patients with intracranial haemorrhages.

1.3 PROJECT SCOPE AND LIMITATIONS

- Dataset Acquisition: Gather a comprehensive dataset of annotated CT or MRI scans containing instances of intracranial haemorrhages. Collaborate with healthcare institutions to access relevant medical imaging data while ensuring patient privacy and data security.
- Data Preprocessing: Preprocess the acquired imaging data to enhance quality, remove noise, and standardize image sizes. Perform augmentation techniques to increase dataset variability and robustness, ensuring effective model training.
- Model Development: Implement the YOLO algorithm for intracranial haemorrhage detection. Customize the architecture and parameters to optimize performance for medical imaging tasks, considering factors such as grid size, anchor boxes, and confidence thresholds.

- Training and Validation: Split the preprocessed dataset into training, validation, and test sets. Train the YOLO model using the training set, fine-tuning parameters, and optimizing performance. Validate the model's performance on the validation set to ensure generalization and avoid overfitting.
- Evaluation Metrics: Evaluate the performance of the trained YOLO model using relevant metrics such as accuracy, precision, recall, F1 score, and area under the ROC curve. Assess the algorithm's ability to detect intracranial haemorrhages accurately and efficiently.
- Optimization and Deployment: Optimize the trained model for speed and efficiency, considering computational resources and real-time processing requirements. Deploy the YOLO-based ICH detection system in healthcare facilities, integrating it into existing medical imaging workflows for seamless operation.
- Validation and Testing: Validate the performance of the deployed system through rigorous testing and validation procedures. Evaluate its effectiveness in detecting intracranial haemorrhages accurately and promptly, ensuring reliability and safety in clinical use.
- Documentation and Reporting: Document the entire development process, including dataset preparation, model training, evaluation results, and deployment procedures. Prepare comprehensive reports and documentation for stakeholders, highlighting the system's capabilities, limitations, and potential impact on patient care.
- Continuous Improvement : Continuously monitor and update the YOLO-based ICH detection system based on feedback from healthcare professionals and ongoing advancements in deep learning and medical imaging technology. Strive for continuous improvement to enhance the system’s performance and utility over time.

Limitations:

- Detection of Small Haemorrhages: YOLO may struggle to accurately detect small or subtle haemorrhages, as its grid-based approach may miss details in densely packed regions or areas with low contrast.
- False Positives in Complex Images: In cases of complex imaging data or artifacts, YOLO may produce false positive detections, leading to erroneous results and potential overdiagnosis.
- Limited Generalization: The performance of YOLO in detecting intracranial haemorrhages may vary across different datasets or imaging modalities, limiting its generalizability to diverse clinical scenarios.
- Interpretability Issues: Deep learning models like YOLO often lack interpretability,

making it challenging to understand the underlying reasoning behind their predictions and potentially hindering trust from healthcare professionals.

- Dependency on Training Data Quality: The effectiveness of YOLO in ICH detection heavily relies on the quality and diversity of the training data. Insufficient or biased training data may lead to suboptimal performance and generalization issues.
- Computationally Intensive: YOLO, particularly in its more recent versions, can be computationally intensive, requiring significant computational resources for training and inference, which may limit its feasibility for deployment in resource-constrained settings.
- Dependency Handling of Class Imbalance: Imbalanced datasets, where the number of haemorrhage cases is significantly smaller than normal cases, may pose challenges for YOLO in maintaining balanced performance across different classes.
- Difficulty in Identifying Subtypes: YOLO may face difficulty in accurately distinguishing between different subtypes of intracranial haemorrhages (e.g., subdural, epidural) due to similarities in appearance and potential overlap in feature representations.
- Regulatory and Ethical Considerations: Deployment of deep learning algorithms like YOLO in clinical settings requires adherence to regulatory guidelines and ethical considerations regarding patient privacy, data security, and model interpretability.
- Integration with Clinical Workflow: Integrating YOLO-based ICH detection into existing clinical workflows may pose challenges, such as compatibility with medical imaging systems, user interface design, and training of healthcare professionals for effective utilization.

Addressing these limitations requires a comprehensive understanding of the capabilities and constraints of YOLO, along with ongoing research efforts to enhance its performance, interpretability, and applicability in real-world clinical settings. Additionally, complementary approaches and collaborative efforts with medical professionals are crucial for mitigating these limitations and advancing the field of intracranial haemorrhage detection.

CHAPTER 2
BACKGROUND WORK

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BACKGROUND WORK

Intracranial haemorrhage (ICH) is a critical medical condition characterized by bleeding within the brain, necessitating swift detection and treatment to mitigate potentially fatal consequences. Deeplearning methods have revolutionized medical imaging by enabling the extraction of intricate patterns from extensive datasets with remarkable efficiency. These methods empower healthcare professionals with advanced diagnostic capabilities, aiding in the timely identification of ICH fromvarious imaging modalities such as CT scans and MRI[1]. By leveraging deep learning algorithms,medical practitioners can expedite the diagnostic process, allowing for prompt intervention and potentially improving patient outcomes[2]. The ability of deep learning models to discern subtle features indicative of haemorrhage within complex imaging data enhances diagnostic accuracy and aids in early intervention strategies[1]. As a result, these technologies play a pivotal rolein augmenting healthcare delivery, particularly in scenarios where rapid decision-making is crucial for patient survival and well-being.

2.1 Existing Method 1: ICH Detection using double branch CNN

2.1.1. Introduction

Intracranial haemorrhage (ICH) relates to bleeding occurring within the intracranial vault. Regardless of the actual cause, a haemorrhage constitutes a major threat. Therefore, an accurate and rapid diagnosis is crucial for the treatment process and its success[1]. ICH diagnosis relies on patient medical history, physical examination, and non-contrast computed tomography (CT) examination of the brain region. CT examination enables bleeding localization and can indicate the primary causes of ICH[1] . There are several challenges related to the ICH diagnosis and treatment: the urgency of the procedure, a complex and time-consuming decision-making process, an insufficient level of experience in the case of novice radiologists, and the fact that most emergencies occur at nighttime. Thus, there is a significant need for a computer- aided diagnosis tool to assist the specialist[1]. Nevertheless, the accuracy of automated haemorrhage detection should be sufficiently high for medical purposes.

2.1.2 Merits, Demerits, and Challenges

Merits

- **Multi-task Learning:** A double branch CNN can be designed to perform multiple tasks[1]. For example, one branch could detect the presence of a haemorrhage while the other determines its type.
- **Different Modalities:** Different branches can be optimized to process different imaging modalities, thereby providing a comprehensive analysis.
- **Rich Feature Extraction:** With two branches, the network can be designed to extract both local and global features, or spatial and contextual features, improving the detection's accuracy.
- **Reduction in False Positives:** By considering different features or tasks in separate branches, the model might be better equipped to reduce false positives.

Demerits

- **Increased Complexity:** Managing a double branch structure can increase the complexity of the network, making it harder to train and optimize.
- **Computational Costs:** Training a double branch CNN might require more computational resources than a single branch network[1].
- **Overfitting Risks:** Due to the additional parameters introduced by the double branch structure, there might be an increased risk of overfitting, especially with smaller datasets.

Challenges

- **Data Requirement:** Training such a complex structure typically requires a large amount of labeled data. In medical imaging, obtaining a sufficient quantity of annotated data can be challenging.
- **Synchronization:** Ensuring that the two branches are in sync and contribute effectively to the final decision can be challenging. It requires careful design and optimization.
- **Interpretability:** Double branch CNNs, like other deep learning models, can act as black boxes, making it hard to interpret their decision-making process. In medical applications, interpretability is crucial for clinical acceptance.
- **Integration with Clinical Workflows:** Designing a system that fits seamlessly into existing clinical workflows without causing disruptions is always a challenge.

- **Generalization:** Ensuring that the model generalizes well across different devices, patient populations, and institutions is crucial.

2.1.3 Implementation

The implementation of Intracranial Haemorrhage (ICH) detection using a double branch CNN requires designing a deep learning model that can process CT scan images (or other imaging modalities) and detect the presence of haemorrhages[1]. The double branch approach can be leveraged to extract different types of features or handle different tasks.

It involves the design and training of a neural architecture that processes medical images through two parallel pathways to extract complementary features or perform simultaneous tasks.The two branches might be tailored to handle different image modalities, capture both local and global image features, or perform separate tasks such as detection and classification of the haemorrhage. Once the input image passes through both branches, the extracted features are merged, often through concatenation or fusion techniques[1]. This combined feature set is then processed by subsequent layers for the final classification or detection of ICH. The implementation necessitates a sufficiently large labeled dataset to train the network and ensure generalizability across various scenarios[2]. Regularization techniques might be employed to mitigate overfitting due to the added complexity of the double branch structure. Upon successful training, the model can be integrated into medical diagnostic systems to aid in the rapid and accurate detection of ICH**.**

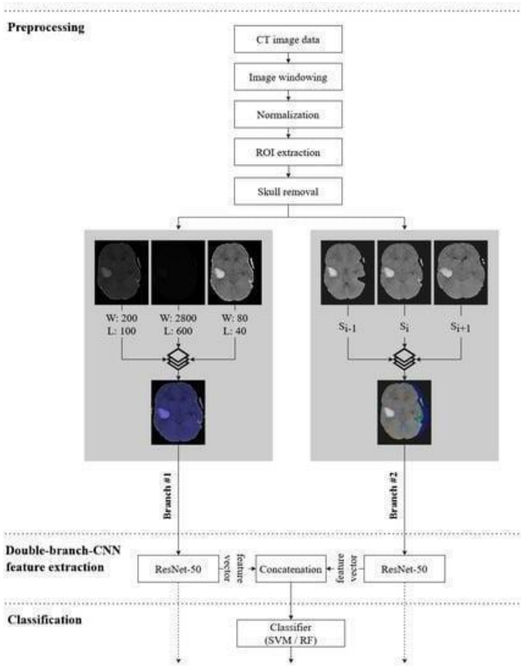


Fig 2.1.1 : ICH detection using Double branch CNN

2.2 Existing Method 2: ICH detection using Parallel Deep Convolutional Models

2.2.1. Introduction

Intracranial Haemorrhage (ICH) is a critical medical condition characterized by bleeding within the brain tissues or cavities. Early and accurate detection of ICH is of paramount importance, as prompt treatment can significantly influence patient outcomes[1]. However, as the complexity ofthe problem and diversity of the data increase, there is a growing need for more sophisticated architectures[2]. One such advancement is the use of parallel convolution models. In this setup, multiple CNN branches operate simultaneously on the input image, often with different kernel sizes or structures. Parallel convolution models and boosting mechanisms offer a potent approachto ICH detection[3]. The parallel convolutions ensure diverse and rich feature extraction, while the boosting mechanism ensures model robustness and improved accuracy by giving higher weight to challenging cases.

2.2.2 Merits, Demerits, and Challenges

Merits

- **Comprehensive Feature Extraction:** Parallel convolution models can extract features at various scales or orientations, making them effective for detecting anomalies that might be missed by a single convolution pathway.
- **Accuracy Improvement:** Boosting mechanisms focus on improving the performance iteratively by concentrating on the errors, which can lead to a more accurate model.
- **Robustness:** The ensemble nature of boosting can increase the robustness of the detection system as it relies on multiple models.
- **Error Reduction:** As boosting gives more weight to previously misclassified examples, it ensures that the algorithm becomes more sensitive to challenging cases, potentially reducing false negatives and false positives.
- **Flexibility:** Parallel convolution pathways can be tailored for specific features or types of haemorrhages, offering flexibility in model design.

Demerits

- **Increased Computational Cost:** Both parallel convolutions and boosting require more computational power and memory due to the increased complexity.

- **Training Time**: With multiple pathways and iterative training for boosting, the training time is generally longer.
- **Risk of Overfitting**: While boosting can improve model accuracy, if not managed correctly, it can also lead to overfitting, especially if the number of boosting rounds is too high.
- **Complexity:** The integration of parallel convolutions with boosting can lead to a complex model, making it more challenging to understand, optimize, and maintain.

Challenges

- **Data Requirement:** Such complex models require substantial labeled data for training, which can be a challenge in the medical domain where annotated data is often scarce.
- **Interpretability:** Deep learning models, especially complex ones like parallel convolution networks combined with boosting, can act as black boxes[2]. In the medical field, interpretability is often a significant concern for clinicians and regulatory bodies.
- **Optimal Architecture Design:** Determining the right number of parallel pathways, their configuration, and how many rounds of boosting to employ can be challenging and might require extensive experimentation.
- **Ensuring Generalizability:** The model should generalize well across different devices, patient populations, and medical institutions. Given the complexity, there might be concerns about how well the model will perform in diverse scenarios.

2.2.3 Implementation

Implementation of Intracranial Haemorrhage (ICH) detection using parallel convolution models and a boosting mechanism involves the simultaneous processing of medical images through multiple convolutional pathways to capture diverse features at various scales or resolutions. Each parallel convolution model extracts distinct features from the input image[3], ensuring comprehensive representation. After feature extraction, a boosting mechanism is employed to sequentially train a series of weak classifiers, where each subsequent classifier focuses on the errors made by its predecessor. This iterative process aims to improve the model's accuracy by giving more emphasis to misclassified instances[4]. The final decision on ICH presence or classification is made by aggregating the outputs of these weak classifiers, often through a weighted majority vote. The combined strength of parallel convolutions, which provide diverse feature representations, and the boosting mechanism, which continually refines the decision boundary, offers a robust approach for accurate and reliable detection of ICH in medical imaging scenarios.

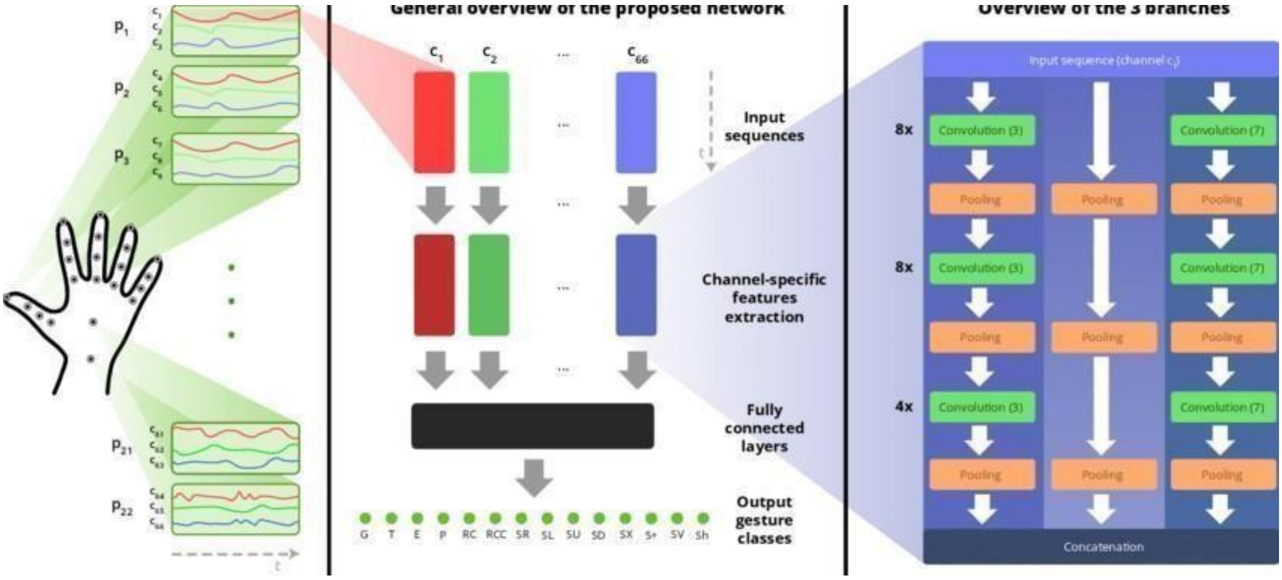


Fig 2.2.1 ICH Detection using parallel deep convolutional models

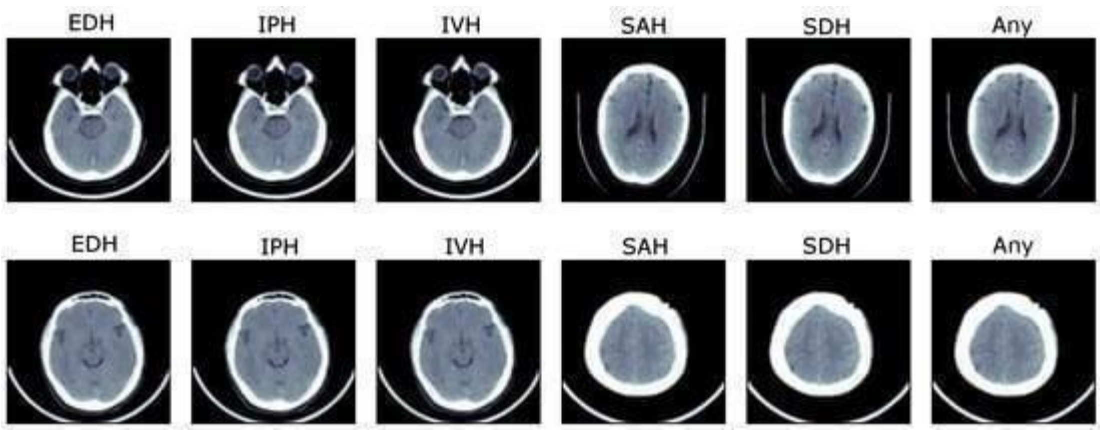


Fig 2.2.2 Representation of subtypes of ICH

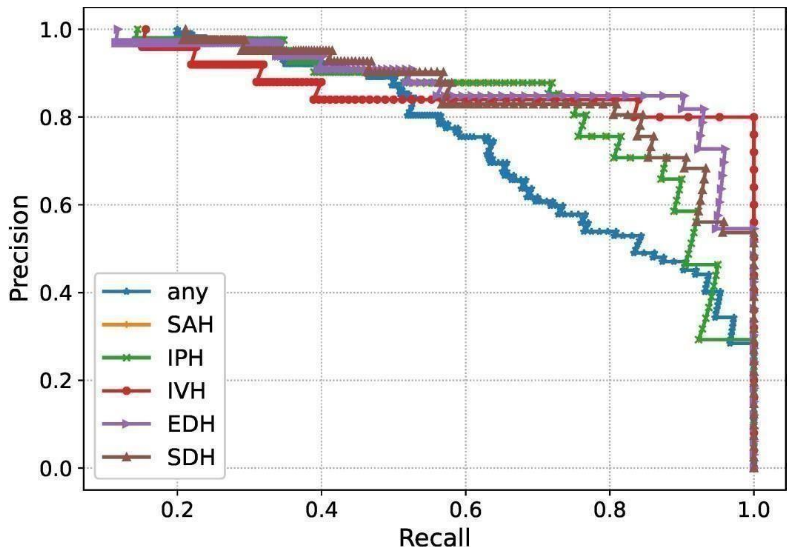


Fig 2.2.3 Precision vs Recall Graph

CHAPTER 3
PROPOSED SYSTEM

CHAPTER 3
PROPOSED SYSTEM

3.1. Objective of Proposed Model

The objective of a proposed model for intracranial haemorrhage detection using the YOLO (You Only Look Once) model would likely be to develop an efficient and accurate system forthe early detection and diagnosis of intracranial haemorrhages from medical imaging data, suchas CT (computed tomography) .

Here are some specific objectives that such a model might aim to achieve:

Early Detection: Detect intracranial haemorrhages as early as possible to facilitate timely medical intervention, which can significantly improve patient outcomes.

Accuracy: Achieve high accuracy in identifying regions of intracranial haemorrhage within medical imaging data to minimize false positives and negatives, ensuring reliable diagnoses.

Efficiency: Develop a model that is computationally efficient and capable of processing medical imaging data quickly, allowing for rapid diagnosis and treatment decisions.

Real-time Detection: Enable real-time or near-real-time detection of intracranial haemorrhages, which is crucial in emergency medical situations where time is of the essence.

Localization and Segmentation: Not only detect the presence of haemorrhages but also accurately localize and segment the affected regions within the brain to provide detailed information to healthcare professionals.

Generalization: Ensure that the model can generalize well to unseen data and different imaging conditions, including variations in imaging quality, patient demographics, and pathology characteristics.

Interpretability: Provide insights into the decision-making process of the model, allowing healthcare professionals to understand why certain regions are identified as haemorrhages and potentially aiding in clinical decision-making.

Integration with Clinical Workflow: Develop a model that seamlessly integrates into existing clinical workflows, allowing for easy adoption by healthcare institutions and practitioners.

Overall, the objective of such a proposed model would be to leverage the capabilities of deep learning, particularly the YOLO model architecture, to create a robust and effective tool for theearly detection and diagnosis of intracranial haemorrhages, ultimately improving patient outcomes and healthcare efficiency.

3.2. Algorithms Used for Proposed Model

YOLO MODEL

YOLO (You Only Look Once) is a real-time object detection algorithm developed by Joseph Redmon and Ali Farhadi in 2015. It is a single-stage object detector that uses a convolutional neural network (CNN) to predict the bounding boxes and class probabilities of objects in input images. YOLO was first implemented using the Darknet framework[3]. The YOLO algorithm divides the input imageinto a grid ofcells, and for each cell, it predicts the probability of the presence of an object and the bounding box coordinates of the object. It also predicts the class of the object. Unlike two-stage object detectors such as R-CNN and its variants, YOLO processes the entire image in one pass, making it faster and more efficient[3]. YOLO has been developed in several versions, such as YOLOv1, YOLOv2, YOLOv3, YOLOv4, YOLOv5, YOLOv6, and YOLOv7. Each version has been built on top of the previous version with enhanced features such as improved accuracy, faster processing, and better handling of small objects[4]. YOLO is widely used in various applications such as self-driving cars and surveillance systems. It is also widely used for real-time object detection tasks like in real-time video analytics and real-time video surveillance.

3.2.1 Working of YOLO Model

The basic idea behind YOLO is to divide the input image into a grid of cells and, for each cell, predict the probability of the presence of an object and the bounding box coordinates of the object. The process of YOLO can be broken down into several steps:

1. Input image is passed through a CNN to extract features from the image.
2. The features are then passed through a series of fully connected layers, which predict class probabilities and bounding box coordinates.
3. The image is divided into a grid of cells, and each cell is responsible for predicting a set of bounding boxes and class probabilities.

4. The output of the network is a set of bounding boxes and class probabilities for each cell.
5. The bounding boxes are then filtered using a post-processing algorithm called non-max suppression to remove overlapping boxes and choose the box with the highest probability.
6. The final output is a set of predicted bounding boxes and class labels for each object in the image.

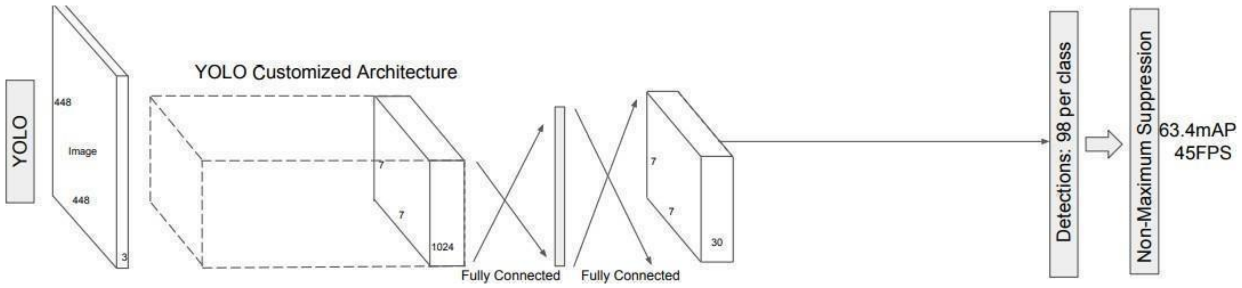


Fig.3.2.1 : Structure of Yolo

3.2.2 Limitations of Yolo:

Even though YOLO is a powerful object detection algorithm, it also has some limitations. Some of these limitations include:

- Limited to object detection: YOLO is primarily designed for object detection and may not perform as well on other tasks such as image segmentation or instance segmentation.
- Less accurate than some other methods: While YOLO is accurate, it may not be as accurate as two-shot object detection methods, such as RetinaNet or Mask R-CNN.
- Struggles with very small objects: YOLO's grid-based approach can make it difficult to detect tiny objects, especially if they are located close to other objects.
- No tracking capability: YOLO does not provide any tracking capability, so it may not be
- suitable for video surveillance applications that require tracking of objects over time.

3.3. Designing

The design stage takes as its initial input the requirements identified in the approved requirements document. For each requirement, a set of one or more design elements will be produced as a resultof interviews, workshops, and/or prototype efforts. Design elements describe the desired softwarefeatures in detail, and generally include functional hierarchy diagrams, screen layout diagrams, tables of business rules, business process diagrams, pseudo code, and a complete entity- relationship diagram with a full data dictionary. These design elements are intended to describe the software in sufficient detail that skilled programmers may develop the software with minimal additional input.

3.3.1. Data Flow Diagram

Data flow diagrams illustrate how data is processed by a system in terms of inputs and outputs. Dataflow diagrams can be used to provide a clear representation of any business function. The techniquestarts with an overall picture of the business and continues by analyzing each of the functional areasof interest. This analysis can be carried out in precisely the level of detail required. The technique exploits a method called top-down expansion to conduct the analysis in a targeted way. As the namesuggests, Data Flow Diagram (DFD) is an illustration that explicates the passage of information in a process. A DFD can be easily drawn using simple symbols. Additionally, complicated processes can be easily automated by creating DFDs using easy-to-use, free downloadable diagramming tools.A DFD is a model for constructing and analyzing information processes. DFD illustrates the flow of information in a process depending upon the inputs and outputs. A DFD can also be referred to as a Process Model. A DFD demonstrates business or technical process with the support of the outside data saved, plus the data flowing from the process to another and the end results.

Fig 3.3.1 Dataflow – level 0

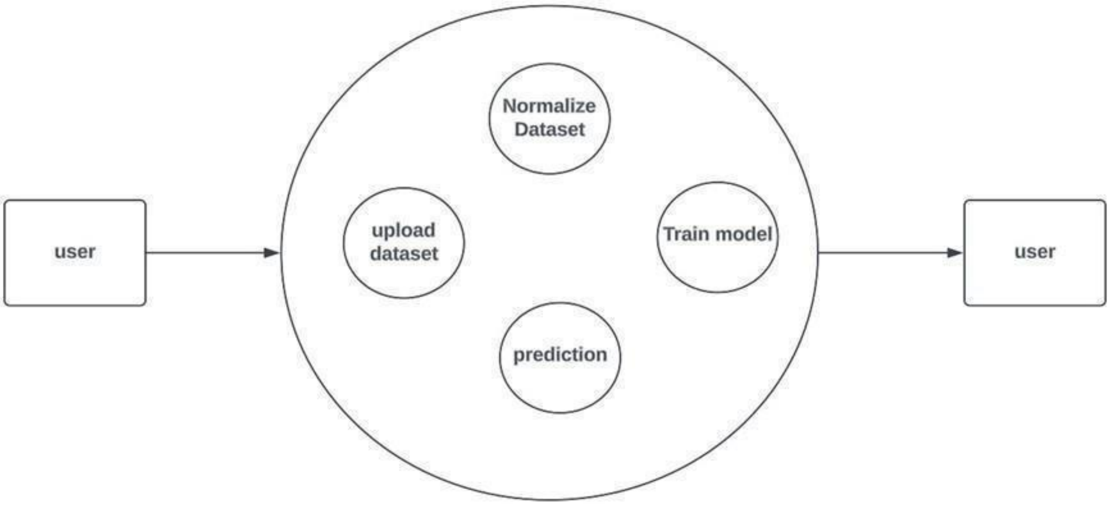


Fig 3.3.2 Dataflow – level 1

3.3.2. Architecture of the project

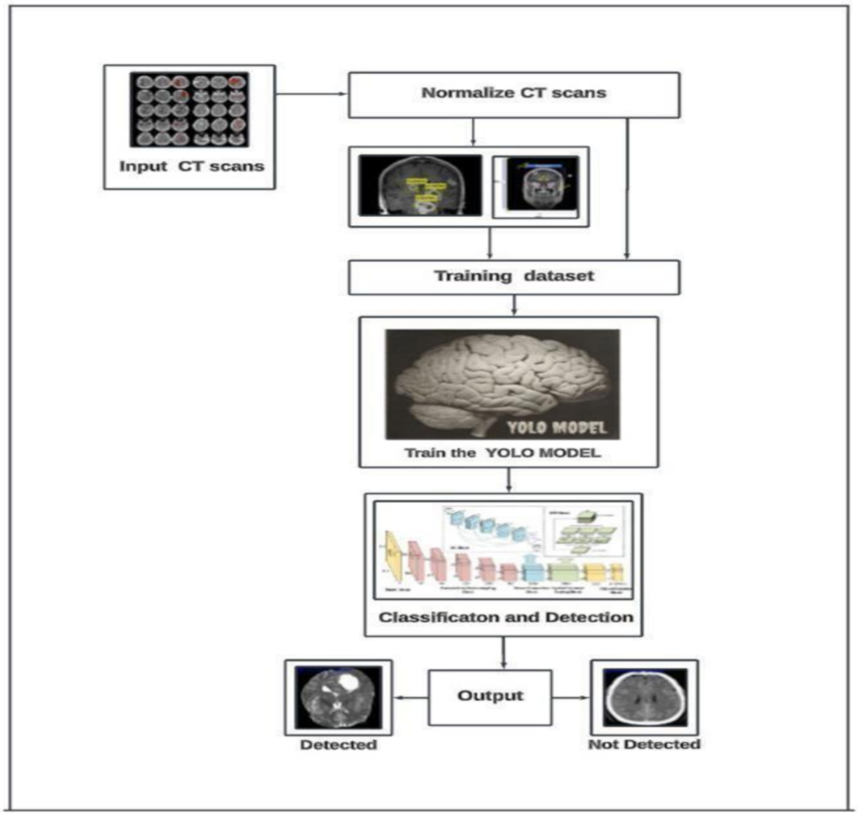


Fig 3.3.3 System Architecture

3.3.3. UML Diagrams

Collaboration Diagram

A collaboration diagram describes interactions among objects in terms of sequenced messages. Collaboration diagrams represent a combination of information taken from class, sequence, and use case diagrams describing both the static structure and dynamic behavior of a system.

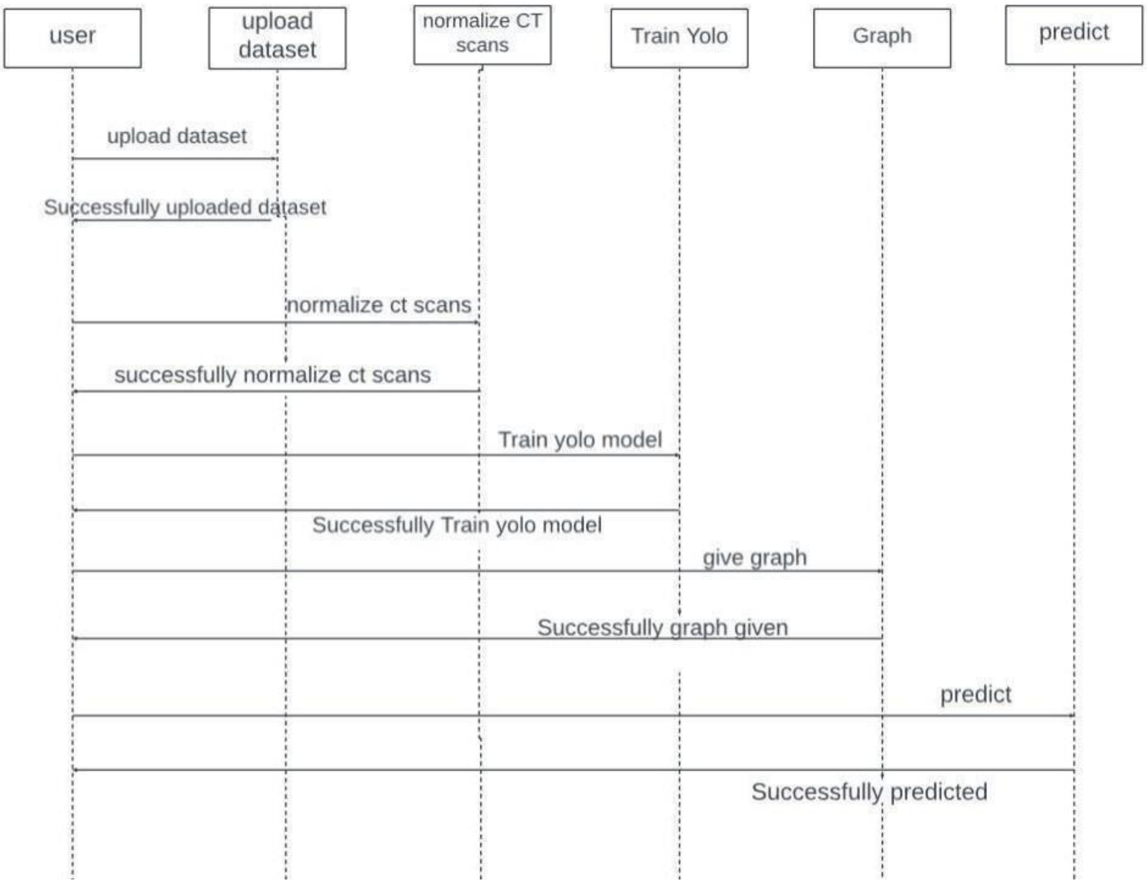


Fig 3.3.4 Collaboration Diagram

3.4 Stepwise Implementation

1. Imports:

-Import necessary libraries such as TensorFlow, NumPy, Seaborn, sklearn, opencv, python, keras, matplotlib, h5py.

-These libraries are used for tasks like deep learning algorithm (TensorFlow, Keras), numerical computations (NumPy), visualization (Seaborn and Matplotlib), for image and video processing(opencv_python),

2. Plotting Dataset:

-Define a function named 'plot_dataset' to visualize the dataset.

-Iterate over a subset of examples from the dataset, plotting images with corresponding labels.

-Each subplot shows an image with its label.

SOURCE CODE:

```
 from tkinter import *

 import tkinter

from tkinter import

filedialog import

matplotlib.pyplot as plt

from tkinter.filedialog import

askopenfilenameimport seaborn as sns

from sklearn.metrics import

precision_scorefrom sklearn.metrics

import recall_score from sklearn.metrics

import f1_score

from sklearn.metrics import

confusion_matrixfrom sklearn.metrics

import accuracy_score

import cv2

import numpy as np
```

```
from keras.utils.np_utils import to_categorical
from keras.layers import MaxPooling2D
from keras.layers import Dense, Dropout, Activation, Flatten
from keras.layers import Convolution2D
from keras.models import Sequential
from keras.models import model_from_jsonimport pickle
import os
from sklearn.model_selection import train_test_split
main = tkinter.Tk()
main.title("Implementation of Deep Learning Based Neural Network Algorithm for IntracranialHemorrhage Detection")
main.geometry("1200x1200")
global filename
global X, Y
global X_train, X_test, y_train, y_test
global model
def uploadDataset():
    global filename
    filename = filedialog.askdirectory(initialdir=".")
    pathlabel.config(text=filename)
    text.delete('1.0', END)
    text.insert(END,filename+" loaded\n\n");
def preprocess():
    global X_train, X_test, y_train, y_test
    global filename
    global X, Y
    text.delete('1.0', END)
    X = np.load('yolomodel/X.txt.npy')
    Y = np.load('yolomodel/Y.txt.npy')
    X = X.astype('float32')
    X = X/255
```

```
indices = np.arange(X.shape[0])
np.random.shuffle(indices)
X = X[indices]
Y = Y[indices]
Y = to_categorical(Y)
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2)
text.insert(END,"Total images found in dataset: "+str(X.shape[0])+"\n\n")
text.insert(END,"Dataset train & test split details\n\n")
text.insert(END,"80% images used to train YOLO model: "+str(X_train.shape[0])+"\n")
text.insert(END,"20% images used to test YOLO model : "+str(X_test.shape[0])+"\n")
text.update_idletasks()
test = X[3]
test = cv2.resize(test, (200,200))
cv2.imshow("Process Sampled Image",test)
cv2.waitKey(0)
def trainYolo():
global model
global X_train, X_test, y_train, y_test
text.delete('1.0', END)
if os.path.exists('yolomodel/yolomodel.json'):
    with open('yolomodel/yolomodel.json', "r") as json_file:
        loaded_model_json = json_file.read()
        model = model_from_json(loaded_model_json)
    json_file.close()
    model.load_weights("yolomodel/yolomodel_weights.h5")
    model._make_predict_function()
else:
    model = Sequential()
    model.add(Convolution2D(32, 3, 3, input_shape = (64, 64, 3), activation = 'relu'))
    model.add(MaxPooling2D(pool_size = (2, 2)))
    model.add(Convolution2D(32, 3, 3, activation = 'relu'))
    model.add(MaxPooling2D(pool_size = (2, 2)))
```

```
model.add(Flatten())

model.add(Dense(output_dim = 256, activation = 'relu'))

model.add(Dense(output_dim = Y_train.shape[1], activation = 'softmax'))

print(model.summary())

model.compile(optimizer= 'adam',loss= 'categorical_crossentropy',metrics=['accuracy'])

hist = model.fit(X_train, Y_train, batch_size=16, epochs=10, shuffle=True, verbose=2)

model.save_weights('yolomodel/yolomodel_weights.h5')

model_json = model.to_json()
with open("yolomodel/yolomodel.json", "w") as json_file:

    json_file.write(model_json)

json_file.close()
      f = open('yolomodel/history.pckl',
'wb')pickle.dump(hist.history, f)
f.close()

predict = model.predict(X_test)

predict = np.argmax(predict, axis=1)

y_test = np.argmax(y_test, axis=1)

for i in range(0,6):

predict[i] = 0

p = precision_score(y_test, predict,average='macro') * 100r

= recall_score(y_test, predict,average='macro') * 100

f = f1_score(y_test, predict,average='macro') * 100a

= accuracy_score(y_test,predict)*100

text.insert(END,'Yolo Model Accuracy : '+str(a)+"\n")

text.insert(END,'Yolo Model Precision : '+str(p)+"\n")

text.insert(END,'Yolo Model Recall    : '+str(r)+"\n")

text.insert(END,'Yolo Model FMeasure : '+str(f)+"\n\n")

text.update_idletasks()

LABELS = ['Normal','Hemorrhage'] conf_matrix
```

```
= confusion_matrix(y_test, predict)

plt.figure(figsize =(6, 6))

    ax = sns.heatmap(conf_matrix, xticklabels = LABELS, yticklabels = LABELS, annot = True,
cmap="viridis" ,fmt ="g");
ax.set_ylim([0,2])

plt.title("Yolo Model Confusion matrix")plt.ylabel('True class') plt.xlabel('Predicted class')

plt.show()

def graph():
    f=open('yolomodel/history.pckl','rb')

    data = pickle.load(f)

    f.close()

    accuracy = data['accuracy']

    loss = data['loss']

    plt.figure(figsize=(10,6))

    plt.grid(True)

    plt.xlabel('Iterations/Epoch')

    plt.ylabel('Accuracy/Loss')

    plt.plot(loss, 'ro-', color = 'red')

    plt.plot(accuracy, 'ro-', color = 'blue')

    plt.legend(['Loss', 'Accuracy'], loc='upper left')

    plt.title('Yolo Model Accuracy & Loss Graph')

    plt.show()

def predict():

    globalmodel

        filename = filedialog.askopenfilename(initialdir="testImages")
        image = cv2.imread(filename)
      img = cv2.resize(image, (64,64))
      im2arr = np.array(img)

      im2arr = im2arr.reshape(1,64,64,3)

      img = np.asarray(im2arr)
```

```
img = img.astype('float32')

img = img/255

preds = model.predict(img)predict = np.argmax(preds)

if predict == 0:
    img = cv2.imread(filename)

    img = cv2.resize(img, (400,400))

    cv2.putText(img, 'No Hemorrhage
    Detected',(10,25),cv2.FONT_HERSHEY_SIMPLEX,0.7, (255, 0, 0), 2)

    cv2.imshow('No Hemorrhage Detected', img)
    cv2.waitKey(0)
if predict == 1:

    img = cv2.imread(filename)

    img = cv2.resize(img, (400,400))

    cv2.putText(img, 'Hemorrhage Detected', (10,25),cv2.FONT_HERSHEY_SIMPLEX,0.7,
    (255, 0, 0), 2)

    cv2.imshow('Hemorrhage Detected', img)
    cv2.waitKey(0)

def close():
main.destroy()

font = ('times', 15, 'bold')

title = Label(main, text='Implementation of Deep Learning Based Neural Network
Algorithmfor Intracranial Hemorrhage Detection')

title.config(bg='brown',

fg='white')title.config(font=font)

title.config(height=3, width=120)

title.place(x=5,y=5)


font1 = ('times', 13, 'bold')

uploadButton = Button(main, text="Upload CT Scans Dataset", command=uploadDataset)

uploadButton.place(x=50,y=100)

uploadButton.config(font=font1)
```

```
pathlabel = Label(main)
pathlabel.config(bg='brown', fg='white')
pathlabel.config(font=font1)
pathlabel.place(x=600,y=100)

processButton = Button(main, text="Normalize CT Scans Images", command=preprocess)
processButton.place(x=350,y=100)
processButton.config(font=font1)

yoloButton = Button(main, text="Train Yolo Model", command=trainYolo)
yoloButton.place(x=50,y=150)
yoloButton.config(font=font1)

graphButton = Button(main, text="Yolo Accuracy-Loss Graph", command=graph)
graphButton.place(x=350,y=150)
graphButton.config(font=font1)

predictButton = Button(main, text="Predict Hemorrhage from Test Image", command=predict)
predictButton.place(x=50,y=200)
predictButton.config(font=font1)

exitButton = Button(main, text="Exit", command=close)
exitButton.place(x=350,y=200)
exitButton.config(font=font1)

font1 = ('times', 12, 'bold')
text=Text(main,height=20,width=90)
scroll=Scrollbar(text)
text.configure(yscrollcommand=scroll.set)
text.place(x=10,y=300)
text.config(font=font1)
main.config(bg='brown')
main.mainloop()
```

1. **Upload Dataset:**

   Define a function upload_dataset() to load your dataset. This function handles tasks like reading image files and their corresponding annotations (if any).

2. **Preprocess Dataset:**

   preprocess_dataset() to perform necessary preprocessing on the dataset. Preprocessing steps include resizing images, normalizing pixel values, and converting annotations to the format suitable for training.

3. **Train Yolo :**

   Define a function def_train_yolo() to create and train a YOLO model. We can either implement YOLO from scratch or use pre-trained models and fine-tune them on your dataset. Libraries like TensorFlow provide pre-implemented YOLO architectures.

4. **Graph :**

   Define a function def_graph() to visualize training progress, such as loss curves, accuracy, and any other relevant metrics. We used libraries like matplotlib or seaborn for plotting.

5. **Prediction:**

   Define a function def_predict() to make predictions using the trained YOLO model. This function takes an input image and return bounding boxes along with confidence scores for detected intracranial hemorrhages.

CHAPTER 4

RESULTS AND DISCUSSION

CHAPTER 4

RESULTS AND DISCUSSION

4.1. Performance metrics

Performance metrics are crucial in assessing the effectiveness of deep learning models, especially in critical applications like medical imaging. When evaluating the performance of deep learning model, YOLO for intracranial hemorrhage (ICH) detection, several metrics are pivotal. Accuracy measures the overall correct classifications, while Sensitivity (or Recall) and Specificity assess the model's effectiveness in identifying true positives and true negatives, respectively. Precision provides insight into the proportion of predicted hemorrhages that are actual cases, and the F1-Score offers a balance between precision and recall. For these object detection frameworks, the Mean Average Precision (mAP) is essential, indicating the model's precision across various types and locations of hemorrhages. Intersection over Union (IoU) evaluates the accuracy of the model's localization by measuring the overlap between predicted and actual bounding boxes. Additionally, false positives and false negatives are crucial for understanding model errors, especially in the critical context of medical diagnostics.

1. **Accuracy:** Accuracy measures the proportion of correctly identified accents out of the total number of samples in the dataset. It provides an overall indication of the model's correctness in predicting accents and is calculated as the ratio of true positive and true negative predictions to the total number of predictions. The formula for Accuracy is as follows:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

2. **Precision:** Precision measures the proportion of correctly identified positive predictions (i.e., correctly identified accents) out of all positive predictions made by the model. It indicates the model's ability to avoid false positives and is calculated as the ratio of true positive predictions to the total number of positive predictions. The formula for precision is as follows:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives + False Positives}}$$

3. **Recall:** Recall, also known as sensitivity, measures the proportion of correctly identified positive predictions (i.e., correctly identified accents) out of all actual positive instances in the dataset. It indicates the model's ability to identify all relevant instances of a particular accent and is calculated as the ratio of true positive predictions to the total number of actual positive instances.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

4. **F1-score:** The F1-score is the harmonic mean of precision and recall and provides a balanced measure of the model's performance across both metrics. It accounts for both false positives and false negatives.

The formula for calculating the F1 score is as follows:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

5. **Confusion Matrix:** The confusion matrix provides a detailed breakdown of the model's predictions compared to the ground truth labels. It shows the number of true positive, true negative, false positive, and false negative predictions, allowing for a more nuanced understanding of the model's performance across different accent classes.

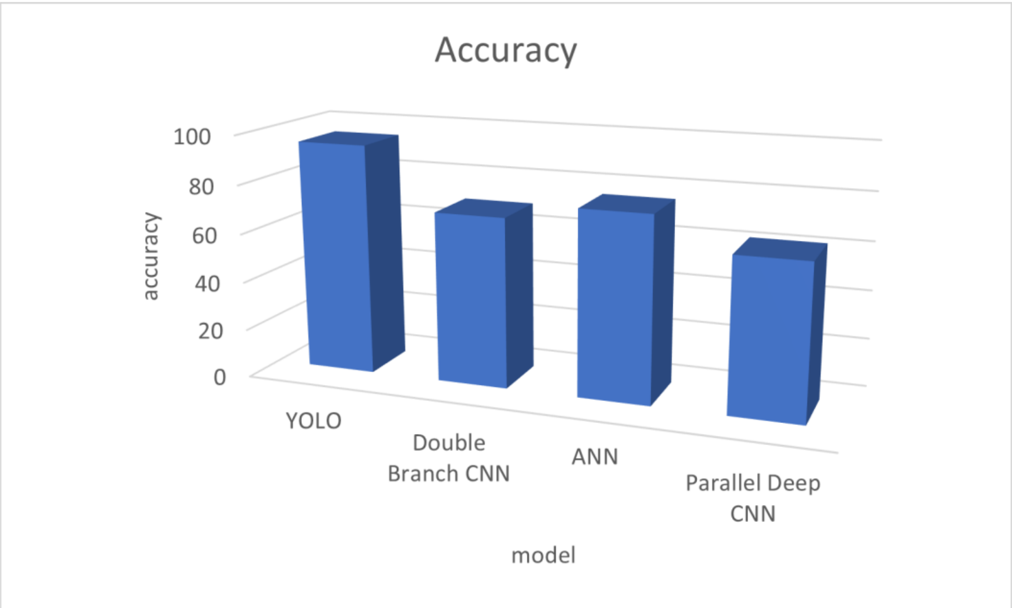


Fig.4.1.1 Accuracy Comparison of Algorithms

4.2. Result

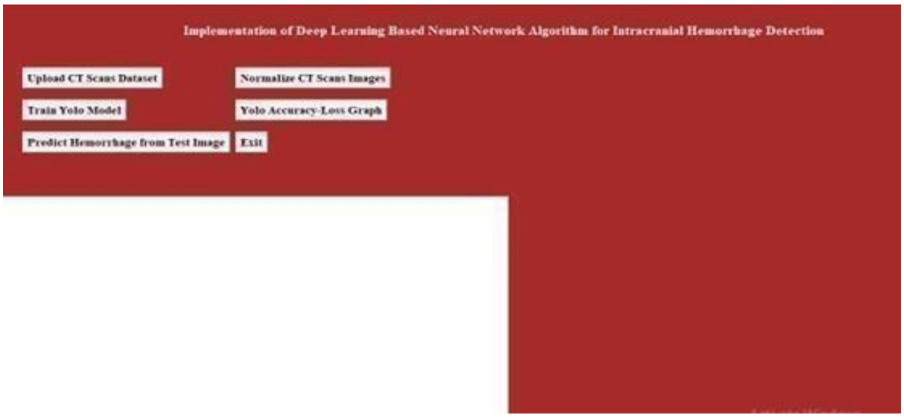


Fig 4.2.1 Uploading the Dataset

- This dataset comprises a collection of medical images categorized into two classes: hemorrhage and non-hemorrhage. These images are typically sourced from medical imaging technologies such as MRI (Magnetic Resonance Imaging), CT (Computed Tomography), or other medical imaging modalities.

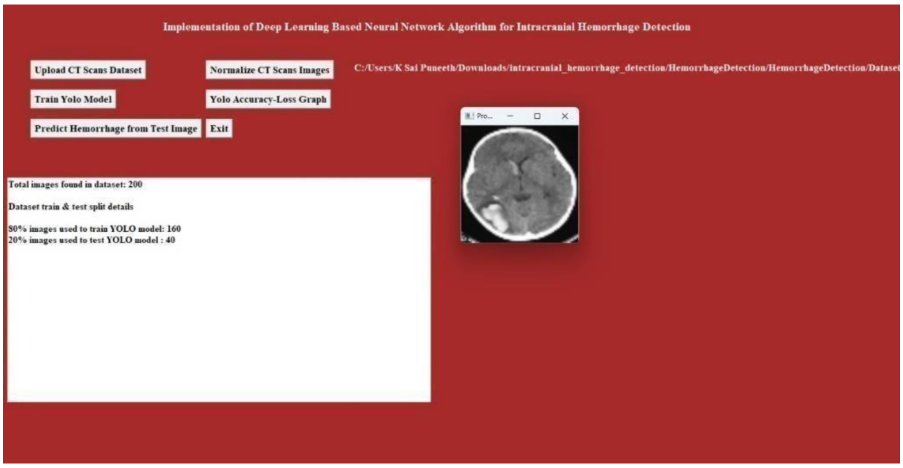


Fig 4.2.2 Normalize images and Train the Yolo

- In this step dataset comprises CT (Computed Tomography) scan images that have undergone a normalization process. Normalization in the context of medical imaging involves standardizing pixel values across images to a common scale or range. This procedure enhances the consistency and comparability of images, which is crucial for accurate analysis and interpretation in medical diagnostics and research. This dataset comprises CT (Computed Tomography) scan images that have been normalized and prepared for training a YOLO

(You Only Look Once) model. YOLO is a popular object detection algorithm known for its real-time processing capabilities and accuracy in detecting object within images.

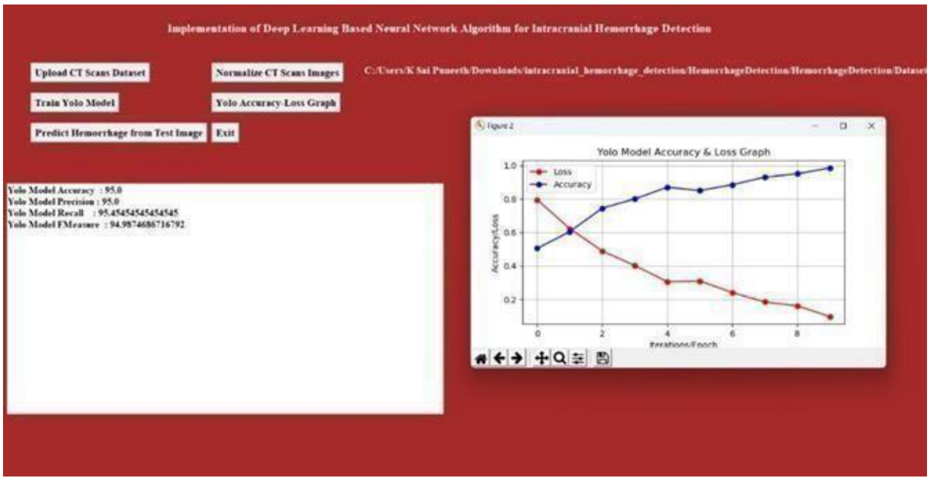


Fig 4.2.3 Yolo Accuracy Graph

- The YOLO (You Only Look Once) model's accuracy and loss are essential metrics used to assess its performance in object detection tasks. Accuracy measures how well the model correctly identifies objects within images, while loss quantifies the disparity between predicted and ground-truth bounding box coordinates and class probabilities.

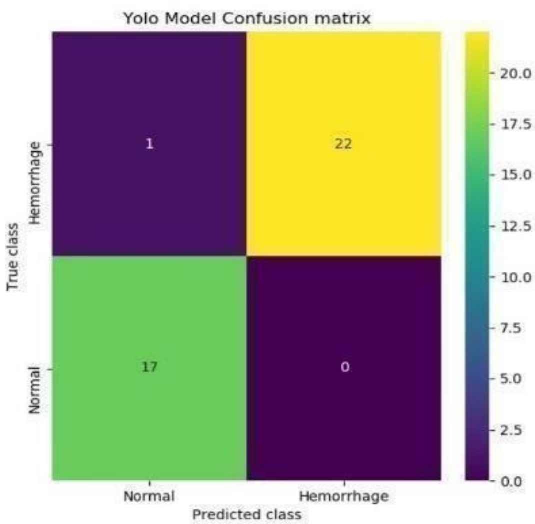
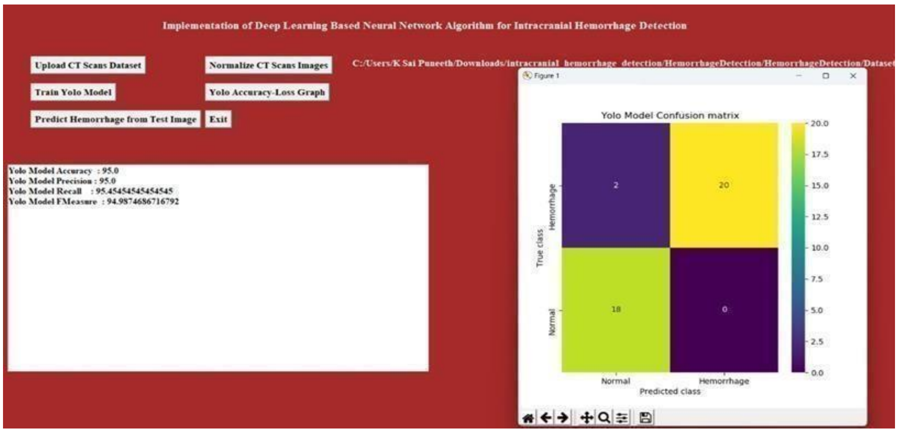


Fig 4.2.4 Confusion Matrix

- A confusion matrix is a tabular representation used to evaluate the performance of a classification model, such as a YOLO (You Only Look Once) model, in distinguishing between different classes. In the context of medical imaging, the confusion matrix can assess the YOLO model's ability to classify CT scan images as either hemorrhage or non-hemorrhage cases.



- Above, we can observe that the YOLO model achieved an accuracy of 92% when applied to the normal and hemorrhage categories, respectively. The x-axis in the confusion matrix represents the predicted classes and the y-axis the original classes. As a result, 20 images were correctly classified as normal, while 2 were incorrectly classified. To submit a test picture and have it recognized for bleeding, close the graph above and then click the "Predict Hemorrhage from Test Image" button.

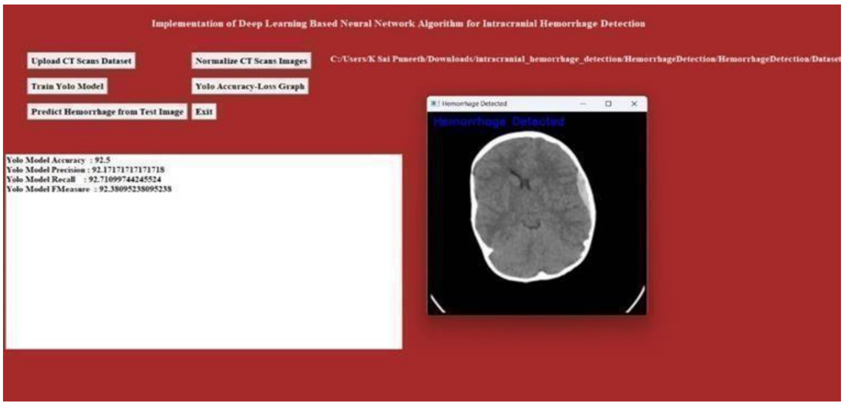


Fig 4.2.5 Predicting the Haemorrhage

- After training a YOLO (You Only Look Once) model on a dataset of CT scan images containing hemorrhage and non-hemorrhage cases, the model can be utilized to make predictions on new, unseen images. These predictions aim to classify whether a given image depicts hemorrhage or non-hemorrhage, assisting in medical diagnosis and treatment planning.

CHAPTER 5

CONCLUSION

CHAPTER 5

CONCLUSION

5.1 Conclusion

In conclusion, the utilization of deep learning methodologies, notably YOLO model, for the detection of Intracranial Hemorrhage (ICH) represents a significant advancement in medical imaging analysis. YOLO, with its end-to-end single-pass architecture, emphasizes speed without substantially compromising detection performance. Yolo model, through its unique architecture and strength facilitate rapid and accurate ICH detection, crucial for timely medical interventions. By integrating these advanced deep learning techniques into the clinical workflow, the potential exists not only to augment the capabilities of radiologists but also to save lives by ensuring swift, informed decisions in critical scenarios. However, the practical implementation of these models necessitates rigorous validation, continuous updates based on the latest data, and careful consideration of ethical implications associated with automated medical diagnoses.

5.2. Future Work

Expanding beyond the current focus on brain hemorrhage, our initiative aims to extend its reach to households, with plans to broaden the scope to encompass other health concerns affecting different parts of the body. As we continue to develop this project for brain hemorrhage, our future endeavors will involve training the model to detect and address potential issues affecting various bodily systems. The Yolo along with RCNN gives the best result, The RCNN, with its region-proposal mechanism, offers a precise means to detect and classify hemorrhages, prioritizing accuracy. In contrast, YOLO, with its end-to-end single-pass architecture, emphasizes speed without substantially compromising detection performance. Both models, through their unique architectures and strengths, facilitate rapid and accurate ICH detection.

CHAPTER 6

REFERENCES

6.1 REFERENCES

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[8] https://images.app.goo.gl/vHrkxdNnsuDHdxdo9

[9] https://youtu.be/ag3DLKsl2vk?si=a3fVsFJzuj45wkwB

[10] https://pypi.org/project/h5py

[11] https://www.kaggle.com

7 GITHUB LINK

https://github.com/Anweshgoud06/Intracranial-Haemorrage-detection

8 PUBLISHED PAPER

www.ijcrt.org © 2024 IJCRT | Volume 12, Issue 3 March 2024 | ISSN: 2320-2882

IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

INTRACRANIAL HAEMORRHAGE DETECTION

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Abstract: : Brain Haemorrhage is the eruption of the brain arteries due to high blood pressure or blood clotting that could cause a traumatic injury or death. Traumatic brain damage or death may occur when the brain's arteries burst open as a result of hypertension or blood coagulation. This is a lifethreatening situation that requires a doctor with extensive training and expertise to pinpoint the source of the internal hemorrhaging and provide treatment without delay. This research proposes the Yolo model, a deep learning algorithm, for the purpose of classifying brain hemorrhages. To improve the deep learning models' accuracy and processing capability, we utilize the dataset of head CT scan pictures. Since large datasets are often unavailable in critical situations, this work primarily aims to apply deep learning's abstraction capacity to a smaller selection of photos. The performance of the proposed approach will be analyzed in terms of accuracy, precision, sensitivity and F1 score. Analyses comparing the Yolo model to balanced and unbalanced datasets further assess the experimental outcomes. By intentionally destabilizing the dataset and achieving maximum precision, yolo is able to provide promising findings.

Keywords – Intracranial Haemorrhage Detection, Yolo Model, Precision, Recall,F1-Score,CADx,ANN,CNN

I. INTRODUCTION

- Brain haemorrhage is the medical term for internal bleeding in the brain. Bleeding in the brain's surrounding tissues as a result of artery rupture or a sudden blockage in the brain's blood supply arteries are the causes of this. Trauma, hypertension, aneurysms, anomalies in blood vessels, amyloid angiopathy, bleeding diseases, brain tumors, and other conditions are the most prevalent causes of brain haemorrhage. Those are the leading reasons for serious disability and death. In 2013, brain hemorrhage accounted for 30% of all fatalities in the US, with a proportion of 100,000:7 in Western nations and 100,000:200 in Asia. In addition, there is a 3:1 female-to-male ratio, and 80% of those with arterial plaque in the brain are born with some degree of vulnerability. The World Health Organisation (WHO) that comprise an ANN are among the hundreds of thousands of unknown variables. The back-propagation method involves iteratively adjusting each weight factor by calculating its delta value using the technique of gradient descent with all or part of the learning data. This process is repeated for each of the hundreds of or more weight variables in the backward direction until the initial training session is complete.

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- Consequently, training an ANN using the back-propagation approach requires a lot of computational resources, even when there isn't a lot of learning data. The novel deep learning techniques algorithm15 uses amounts of chosen delta-values within the specified range to adjust at random weight factors as well as bias values. This is in contrast to the computing-intensive gradient-descending method, in which the average error in training for all the learning information in the present ANN is only calculated in the forward direction. In order to minimize the training errors for learning data, the method sets the weight factors and bias parameters of the ANN throughout the training session using a random optimization process. As a result, algorithm 15 is easy to grasp, straightforward, and very effective.
- Research on the effectiveness of the new deep-learning algorithm as a diagnostic tool in the field of emergency neuroradiology is lacking. This study set out to examine the diagnostic performances of an algorithm that does not use convolutional neural networks (CNN), the most popular deep learning method for image recognition at the moment, in detecting intracerebral haemorrhage (ICH) and categorising it into three subtypes: epidural/subdural, subarachnoid, and intraventricular haemorrhage (IVH). Based on the cerebral height, CT scans were segmented into 10 subdivisions for this investigation. For each instance, the CT pictures from a subdivision were combined into one image. This groundbreaking research was the first of its kind to evaluate the diagnostic performance for ICH detection and subtyping for each CT image subdivision. In order to evaluate our method's diagnostic efficacy in comparison to existing CNN-based techniques, we combined all of the CT scans from each patient into a single picture, independent of the intracranial part's height, and conducted experiments.

II. Related Work

A. Hemorrhage associated mechanisms of neuroinflammation in experimental traumatic brain injury:

Over 3.17 million Americans suffer from traumatic brain injury (TBI), a condition that is receiving more and more attention from the general public. Improving TBI diagnosis and therapy requires immediate insight into the disease's fundamental process. The progressive processes of brain damage in a mild fluid concussion injury model were investigated here under the notion that cerebral hemorrhagic coagulation and later immune cell infiltration cause the harm. A hematoma in the subdural region and a hemorrhagic brain injury are indicated by this. As the strain on the wounded brain grew, we saw more hemorrhagic lesions and infarct volume. The bio-distribution of a fluorescent tracer in the cerebrospinal fluid (CSF) route after the injury further confirmed the amount of the bleeding. The tracer's bio distribution was reduced near the location of hemorrhage due to coagulation, which prevented the tracer from moving between tissues and the cerebrospinal fluid (CSF). The cause for this blockage was established by more coagulation factor XII expression and the death of necrotic cells close to the impact site. A variety of indicators, such as the buildup of immune cells and the death of neurons, demonstrated that the production of neuroinflammation as well as neurodegeneration within the impact site was significantly aided by the breakdown of the blood-brain barrier. Based on our findings, neurodegeneration and onsite perivascular inflammation are consequences of immediate hemorrhagic damage caused by coagulation involved brain blood vessel ruptures. Therapeutic treatment development in traumatic brain injury (TBI) might benefit from a knowledge of this sequential process. Abstract Visual Fundamental processes in moderate to severe blunt traumatic brain injury: coagulation, coagulant necrosis, and immediate immune cell infiltration are caused by bleeding that follows cerebrovascular disturbance.

IJCRT2403540 | International Journal of Creative Research Thoughts (IJCRT) www.ijcrt.org | e2

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B. Combining symmetric and standard deep convolutional representations for detecting brain haemorrhage:

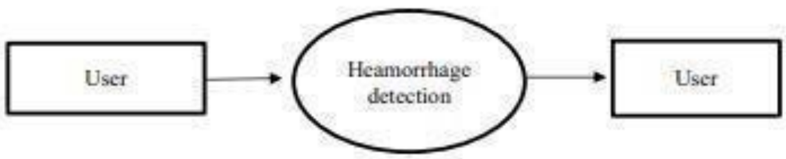
A severe kind of stroke, brain hemorrhage (BH) has a high rate of death and disability. Neuroimaging techniques, such computed tomography (CT), are often used for the detection & diagnosis of BH. For the purpose of BH detection using CT imaging, we evaluate and contrast symmetry-aware and symmetry-naive feature representations, as well as combinations of the two. In terms of area under the curve (AUC) for BH identification, one of the suggested designs, e-DeepSymNet, gets 0.99 [0.97-1.00]. A comparison of the activation levels reveals that the two representations one symmetry-aware and one symmetry-naïve offer complementing information, with the symmetry-aware representation naive accounting for 20% of the total predictions.

C. A GLCM embedded CNN strategy for compute raided diagnosis in intracerebral haemorrhage:

Radiologists may benefit from computer-assisted diagnosis (CADx) systems as they categorize various medical pictures, such as CT and MR scans. A key component of CADx at the moment is convolutional neural networks. Nevertheless, radiologists often find it challenging to directly apply CNN algorithms to the irregular segmentation ROIs that pique their curiosity, as CNN models typically need square-like inputs. We provide a novel method for building the model in this study. First, we take the data from the irregular area and transform it to a fixed-size Gray-Level Overlap Matrix (GLCM). Then, we feed this GLCM into our CNN model. As a helpful complement to the initial CNN, CNN also extracts a handful additional features based on GLCM. At the same time, the network will improve its classification accuracy by focusing on the critical lesion neighborhood. Our novel model is tested on three different classification databases: Cervix, Hemorrhage, and BraTS18 in order to confirm its applicability to all cases. Using test loss and accuracy in classification as metrics for assessment, the suggested framework ultimately surpasses the equivalent state-of-the-art algorithms across all databases.

III .Methods And Experimental Details

- In contrast to machine learning algorithms, deep learning algorithms automatically extract aspects of targets, making them more helpful. In this project, we are using the Yolo model. Bleeding within the skull, also known as intracranial hemorrhage, is a medical emergency that needs immediate and, in many cases, extensive care. An immediate procedure is necessary for the diagnosis. Experts examine MRI scans of the brain to detect the existence, location, and kind of hemorrhage in patients exhibiting acute neurological signs \ such as severe headaches or loss of consciousness. It may be a lengthy and difficult procedure. In order to improve the accuracy of the findings and ensure that patients get timely treatment, we will apply a novel algorithm to the CT scan dataset designed to identify hemorrhage. To improve the efficiency of the final results, we will employ various picture identification and processing methods.



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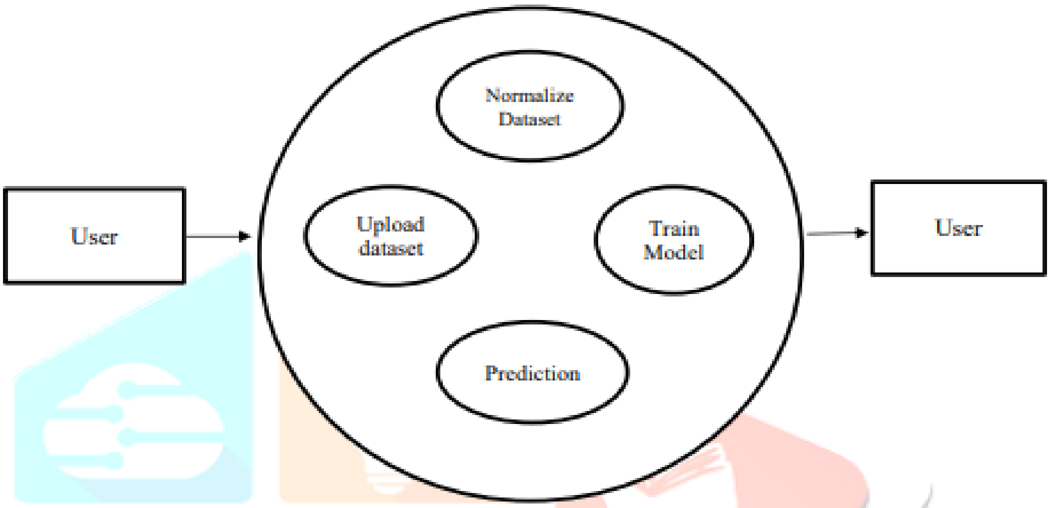

Yolo Algorithm :

- Joseph Redmon, a computer scientist, and Ali Farhadi created the You Only Look Once (YOLO) algorithm in 2015 to identify objects in real-time. It identifies objects in input photos by predicting their bounding boxes and probability classes using a network of convolutional neural networks (CNN). It acts as a single-stage object detector.First, we need to figure out what the predictions are for the YOLO algorithm to work. Predicting an object's class and the area within it that defines its position is our ultimate goal. You may use four different adjectives to describe each bounding box: at the middle of a box's perimeter (bxby) two. breadth (bw) height, in feet class of an item (such as a vehicle, a set of traffic signals, etc.) corresponds to value cis. Read our breakdown of the ways in which PP-YOLO outperforms YOLOv4 to find out more about PP-YOLO, also known as Paddle Paddle YOLO, an upgrade on YOLOv4.Not only is it easy to build, but it can also train on entire pictures directly. YOLO is a more deserving, quick, and resilient algorithm than Faster R-CNN because it provides a more generalizing representation of objects. Because of these remarkable benefits, this algorithm is highly recommended and stands out. This study used a novel deep- learning algorithm to detect ICH on summed CT images without using CNN or the three-dimensional approach, in contrast to previous research that used the back-propagation method and CNN to identify ICH on individual CT images. A research that used tailored CNNs based on ROI for hemorrhage detection demonstrated an improved area under the curve (AUC) of 0.983, along with a sensitivity of 97.1% and a specificity of 97.5%2. The area under the curve (AUC) for identifying hydrocephalus, mass effect, and hemorrhage was 0.91 in another investigation, with a sensitivity of 90% and a specificity of 85.0%5. Although these studies demonstrated impressive diagnostic accuracy for certain photos, its applicability in broader emergency scenarios is limited. Data selection and preparation for the input scans may be crucial, and the application can be reliant on the kind of CT scanner employed. Using relatively small datasets we were able to get equivalent performance outcomes in our investigation. Furthermore, our method has the benefit of eliminating the need for expert-level preprocessing, allowing for full automation and integration into the computed tomography (CT) machine. So, in a real-life emergency situation, our method may significantly cut down on the time it takes to diagnose ICH without the assistance of a physician.

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DATA SETS

- **Normal Data:** Normal data which its tells about the reports and the data are the normal.


- **Haemorrhage Data:** Hemorrhage Data which it predicts the bleeding point and analyze the data and tells the accuracy data.


IV.RESULTS AND DISCUSSION

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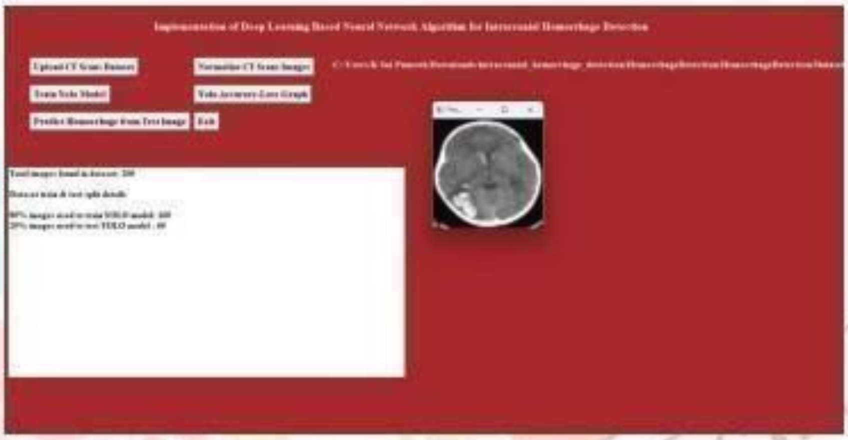
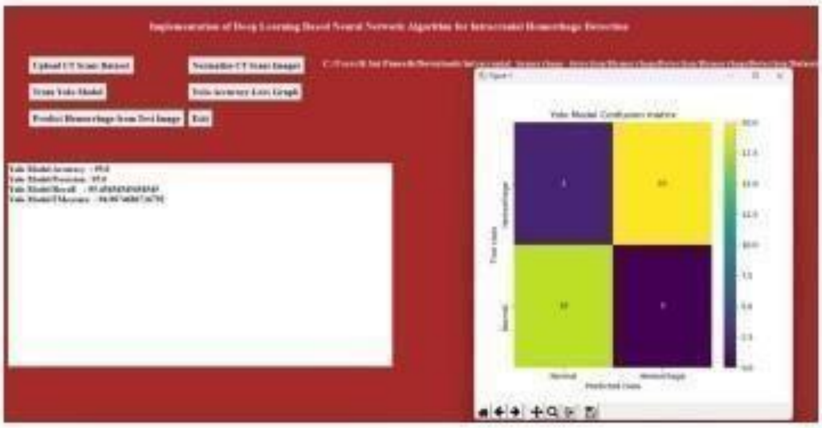


The software is using 80% of the photographs (160 total) for training and 20% (40 total) as testing, using one sample. This information is shown in the preceding screen. No less than two hundred photos make up the dataset. After that, save the image and then close the old one. Select "Train Yolo Model" to begin training the model. The outcome that follows is shown below.



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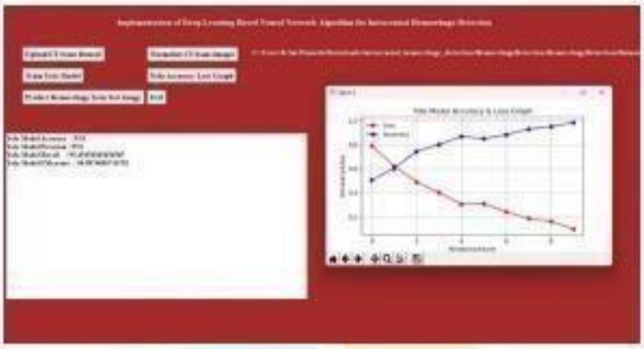

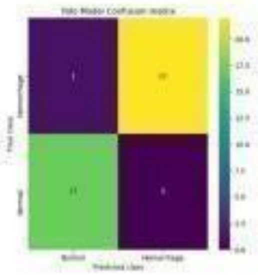

Above, we can observe that the YOLO model achieved an accuracy of 92% when applied to the normal and hemorrhage categories, respectively. The x-axis in the confusion matrix represents the predicted classes and the y-axis the original classes. As a result, 20 images were correctly classified as normal, while 2 were incorrectly classified. To submit a test picture and have it recognized for bleeding, close the graph above and then click the "Predict Hemorrhage from Test Image" button.

- Detection of hemorrhage is shown in blue text on the upper screen; you may submit and test more photos in the same way.

No sign of bleeding can be seen in the photograph up above.

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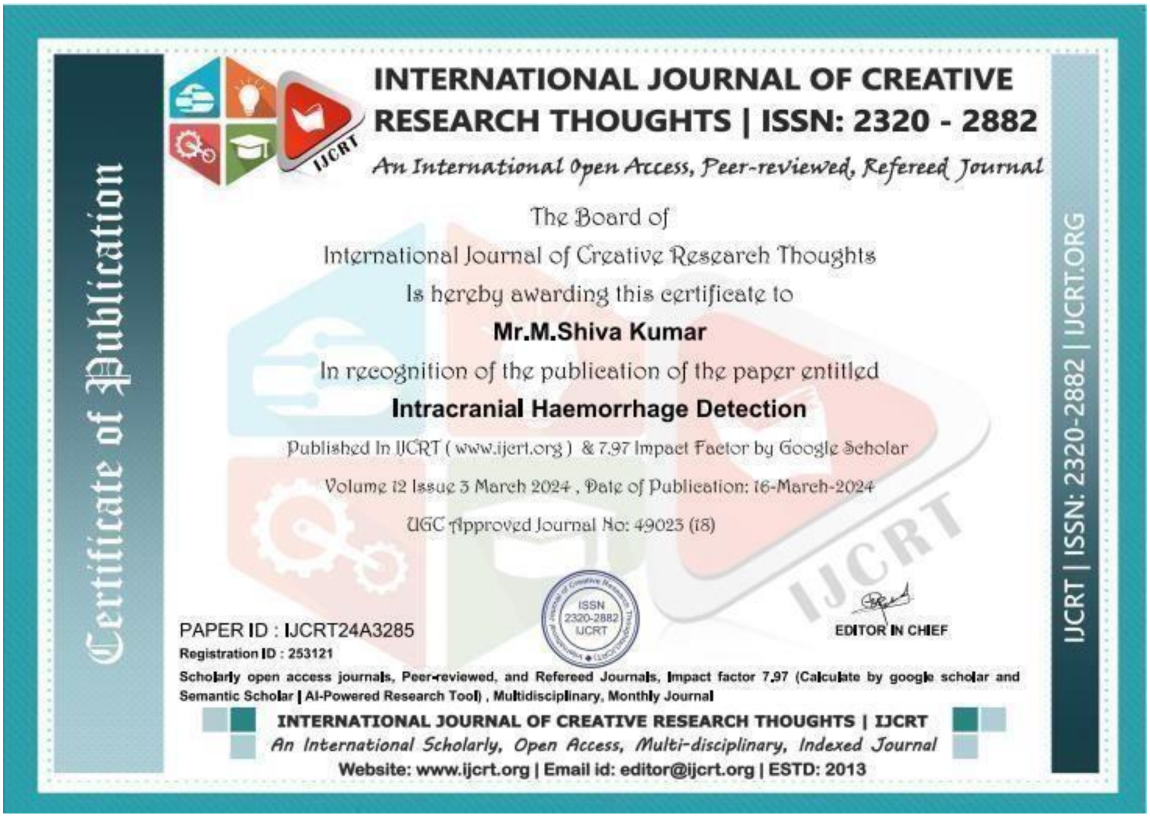
9 CERTIFICATES: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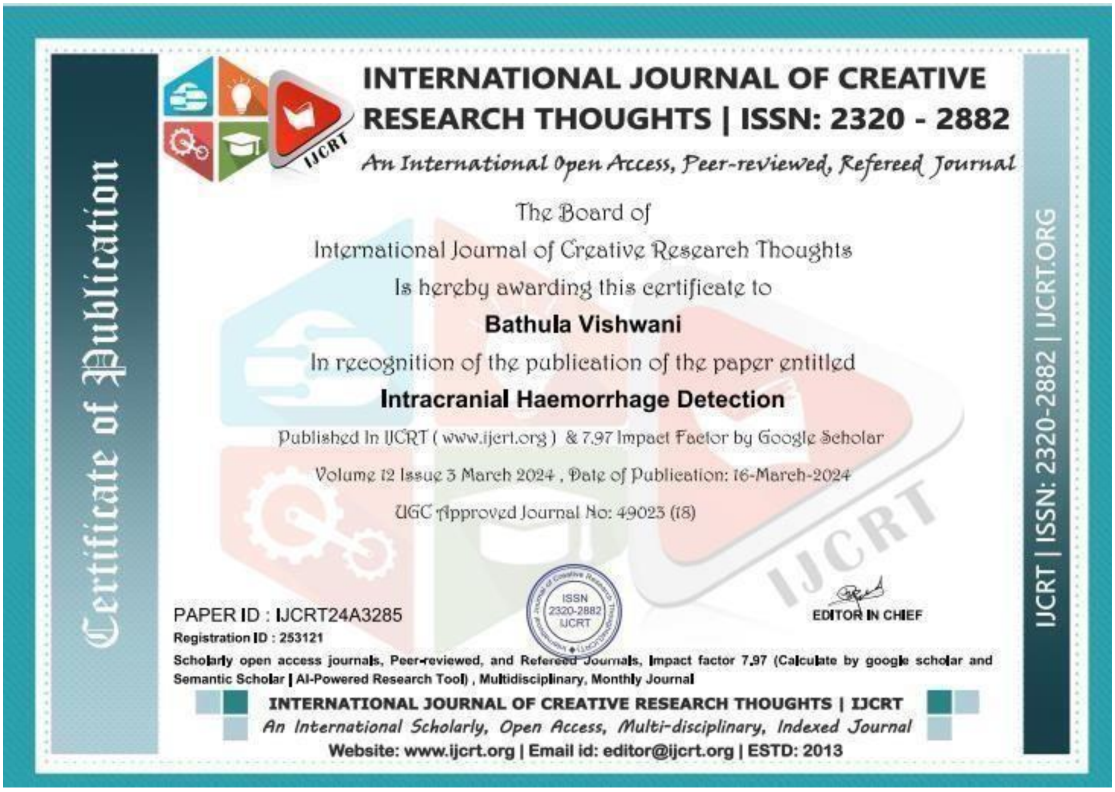
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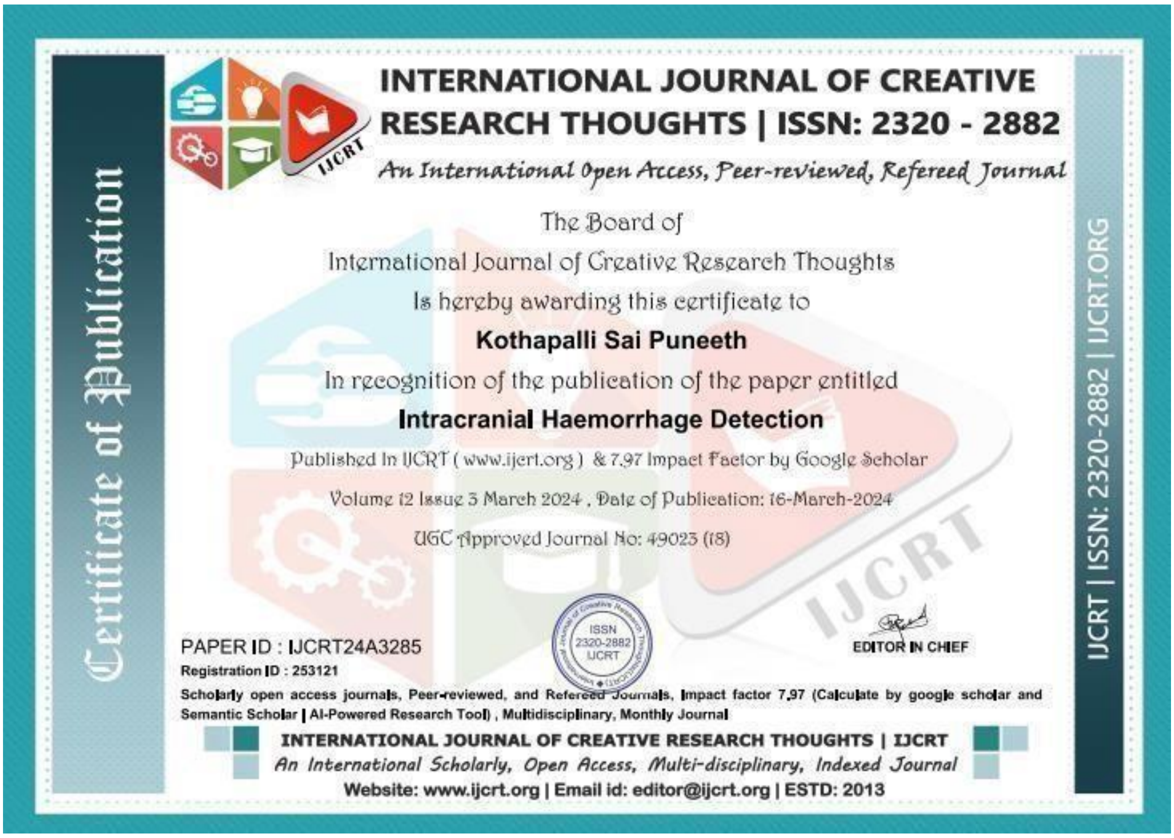
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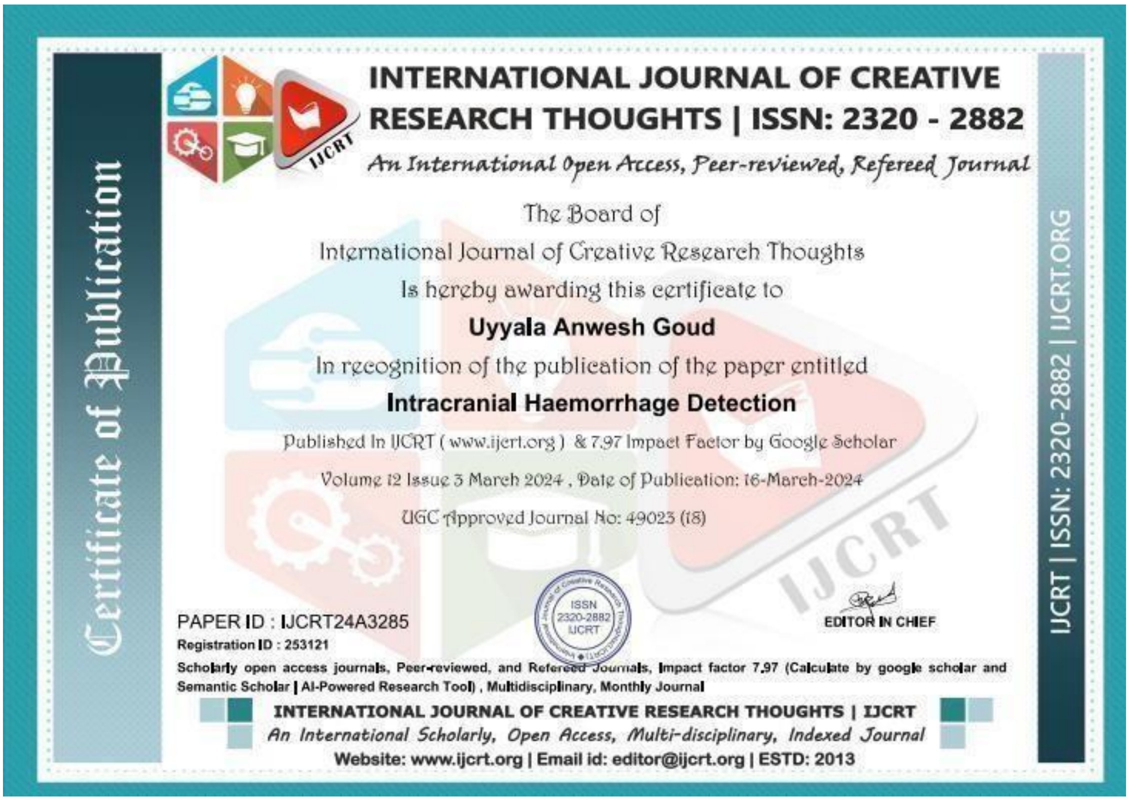
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