MULTI-MODEL MEDICAL IMAGE CLASSIFICATION AND DETECTION USING DEEP NEURAL NETWORK

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AD18811 – PROJECT WORK

Viva Voce Examination

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Domain	: DATA ANALYTICS

ABSTRACT

- In healthcare, the mission is to elevate patient outcomes through proactive medical image classification and detection.
- Employing ResNet models, the project focuses on X-ray images (elbow, hand, shoulder) for swift orthopedic diagnoses, determining bone fractures accurately.
- Extending the scope, a YOLOv8 architecture classifies brain MRI images into glioma, meningioma, pituitary tumors, and identifies cases with no tumor, significantly advancing early neurological diagnoses.
- A secondary YOLOv8 architecture categorizes incoming medical images (brain MRI, elbow X-ray, hand X-ray, shoulder X-ray), directing them to the corresponding models for specialized diagnostic algorithms.
- The holistic approach ensures seamless integration into healthcare systems, offering a robust solution for multi-model medical image classification and tumor detection, promising significant advancements in diagnostic data analytics.

PROBLEM STATEMENT

- Developing a robust predictive model for medical image analysis is crucial, aiming to accurately identify conditions from X-rays and MRI scans.
- Challenges involve addressing issues related to image resolution, anatomical structure variations, and overlaps.
- Consistent accuracy in diagnostic models is paramount.
- The ultimate goal is to advance patient care through timely and accurate predictions, improving medical image analysis.
- Conditions include fractures in elbow, hand, and shoulder bones, as well as glioma, meningioma, pituitary tumors, and the absence of tumors in brain MRI images.

INTRODUCTION TO BASIC CONCEPTS

- **DNN:-** Deep Neural Networks (DNNs) serve as powerful tools in various domains, including image classification and detection, by employing multiple layers of interconnected nodes to extract intricate features from raw data. DNNs offer exceptional capabilities in pattern recognition and object detection, making them indispensable for tasks like medical image analysis, where accurate diagnostics are paramount.

- **ResNet:-** ResNet, or Residual Networks, revolutionize deep learning by addressing vanishing gradient problems. With shortcut connections, ResNet allows the training of exceptionally deep neural networks. In image classification, ResNet architectures capture intricate details, enhancing accuracy and performance.

- **YOLOv8:-** YOLOv8 (You Only Look Once version 8) is a state-of-the-art object detection architecture. Renowned for its speed and accuracy, YOLOv8 processes images in a single pass, detecting objects with remarkable efficiency. It excels in various applications, including medical image analysis, providing rapid and reliable detection.

LITERATURE REVIEW (1/6)

- F. Mohammad, S. Al-Ahmadi and J. Al-Muhtadi, (2023), "**Block-Deep: A Hybrid Secure Data Storage and Diagnosis Model for Bone Fracture Identification of Athlete From X-Ray and MRI Images**", IEEE Access, Vol. 11, pp. 142360-142370

Problem Statement:

- Traditional bone fracture detection methods are costly and prone to inaccuracies. Security concerns in existing machine learning methods for athlete data persist.
- Machine learning approaches, while effective in bone fracture detection, lack robust security mechanisms for athlete data during diagnostics.

Methodology:

- The paper proposes a hybrid model integrating blockchain and deep learning for precise bone fracture detection and athlete data security.
- Key steps include data collection, blockchain-based security, feature extraction via Capsule Network, and final classification using Visual Transformer-based transfer learning..
- Experimental evaluation showcases the model's excellence, achieving accuracy values of 95.01%, 94.04%, and 96.25% on different datasets, surpassing state-of-the-art methods.

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LITERATURE REVIEW (2/6)

- K. Neamah, F. Mohamed, et al., (2023), "**Brain Tumor Classification and Detection Based DL Models: A Systematic Review**", IEEE Access, Vol. 12, pp. 2517-2542.

Problem Statement:

- Deep learning's impact on biomedical sectors, particularly in brain tumor identification via MRI scans, requires a focused review.
- Despite successes, a comprehensive exploration is crucial to guide researchers in leveraging deep learning for effective brain tumor detection.

Methodology:

- This research project examines previous studies using deep learning for brain tumor identification via MRI scans.
- The study provides an overview of brain tumor detection studies and analyzes deep learning studies from 2019 to 2022, presenting findings in a tabular format.
- Notable findings highlight ResNet (99.06%), Googlenet (98.45%), EDCNN (97.77%), CSO (98.68%), YOLOv5 (98.87%), among others, as highly utilized and trusted methods in 2022.

LITERATURE REVIEW (3/6)

- Z. Atha and J. Chaki. (2023), "**SSBTCNet: Semi-Supervised Brain Tumor Classification Network**", IEEE Access, Vol. 11, pp. 141485-141499.

Problem Statement:

- Classifying brain tumors from Magnetic Resonance Imaging (MRI) poses a vital yet challenging task in diagnosis.
- Despite favorable results from current Deep Learning (DL) methods, challenges arise in cases where visual representations of non-brain tumor and brain tumor regions are indistinguishable.

Methodology:

- A novel Semi-Supervised Brain Tumor Classification Network (SSBTCNet) combines unsupervised AutoEncoder (AE) with supervised networks, improving brain MRI classification with accuracy rates (92.26%).
- Efficiency is enhanced with a fuzzy-logic-based method for generating enhanced instances and utilizing augmented unlabeled data, demonstrating superior performance.

LITERATURE REVIEW (4/6)

- R. Zaitoon and H. Syed, (2023). "**RU-Net2+: A Deep Learning Algorithm for Accurate Brain Tumor Segmentation and Survival Rate Prediction**", IEEE Access, Vol. 11, pp. 118105-118123.

Problem statement:

- Brain tumors pose significant challenges in diagnosis and treatment, necessitating advanced techniques.
- Deep learning, an evolving approach, offers promise in automating brain tumor diagnosis.

Methodology:

- The novel deep-learning framework for brain tumor diagnosis employs a multi-step process, including data acquisition, pre-processing with Convolutional Normalized Mean Filter (CNMF), and multi-class classification using the DBT-CNN classifier model.
- Subsequent steps involve tumor demarcation with the RU-Net2+ model, feature extraction using the Cox model, and patient survival rate prediction with a logistic regression model. Experimental results on the BraTS dataset showcase exceptional performance with accuracy of (97.7%), surpassing benchmarks in accuracy and precision.

LITERATURE REVIEW (5/6)

- G. Moon, S. Kim, W. Kim, et al., (2022), "**Computer Aided Facial Bone Fracture Diagnosis (CA-FBFD) System Based on Object Detection Model**", IEEE Access, Vol. 10, pp. 79061-79070.

Problem Statement:

- Early diagnosis of facial bone fractures is critical to prevent complications, but the analysis of CT images is time-consuming and lacks specialists.
- Current classification-based studies struggle with pinpointing exact fracture locations, while object detection-based approaches face challenges due to the ambiguous shape of fractures.

Methodology:

- The proposed computer-aided facial bone fracture diagnosis (CA-FBFD) system adopts the YoloX-S object detection model trained with IoU Loss for box prediction and CT image Mixup data augmentation.
- Exclusively trained on nasal bone fracture data, the CA-FBFD system achieves an impressive average precision of 69.8% for facial fractures during evaluation, surpassing the baseline YoloX-S model by 10.2% and demonstrating a sensitivity/person of 100%.

LITERATURE REVIEW (6/6)

- L. Mu, T. Qu, et al., (2021), "**Fine-Tuned Deep Convolutional Networks for the Detection of Femoral Neck Fractures on Pelvic Radiographs: A Multicenter Dataset Validation**", IEEE Access, Vol. 9, pp. 78495-78503.

Problem Statement:

- Efficient femoral neck fracture detection on radiographs for emergency patients is crucial but challenging.
- Existing methods lack accuracy and efficiency, necessitating the development of an advanced detection system.

Methodology:

- Retrospective collection of 1,491 frontal pelvic radiographs for fine-tuning and validating the Digital Radiography Fracture Detection System (DR-FDS) on a primary dataset.
- Evaluation involves internal and external test sets, computing per-bounding box recall, precision, per-image sensitivity, specificity, and Area Under the Receiver Operating Characteristic (ROC) curve (AUC). The fine-tuned DR-FDS demonstrates improved overall performance, achieving high AUC values and showing significant improvements in specificity, sensitivity, and accuracy (95.2%) for clinicians identifying minimal/undisplaced fractures.

ISSUES AND CHALLENGES

- Managing vast medical image datasets raises storage constraints and training time issues. High-resolution X-rays and MRI scans demand efficient storage, necessitating optimization for timely model deployment.

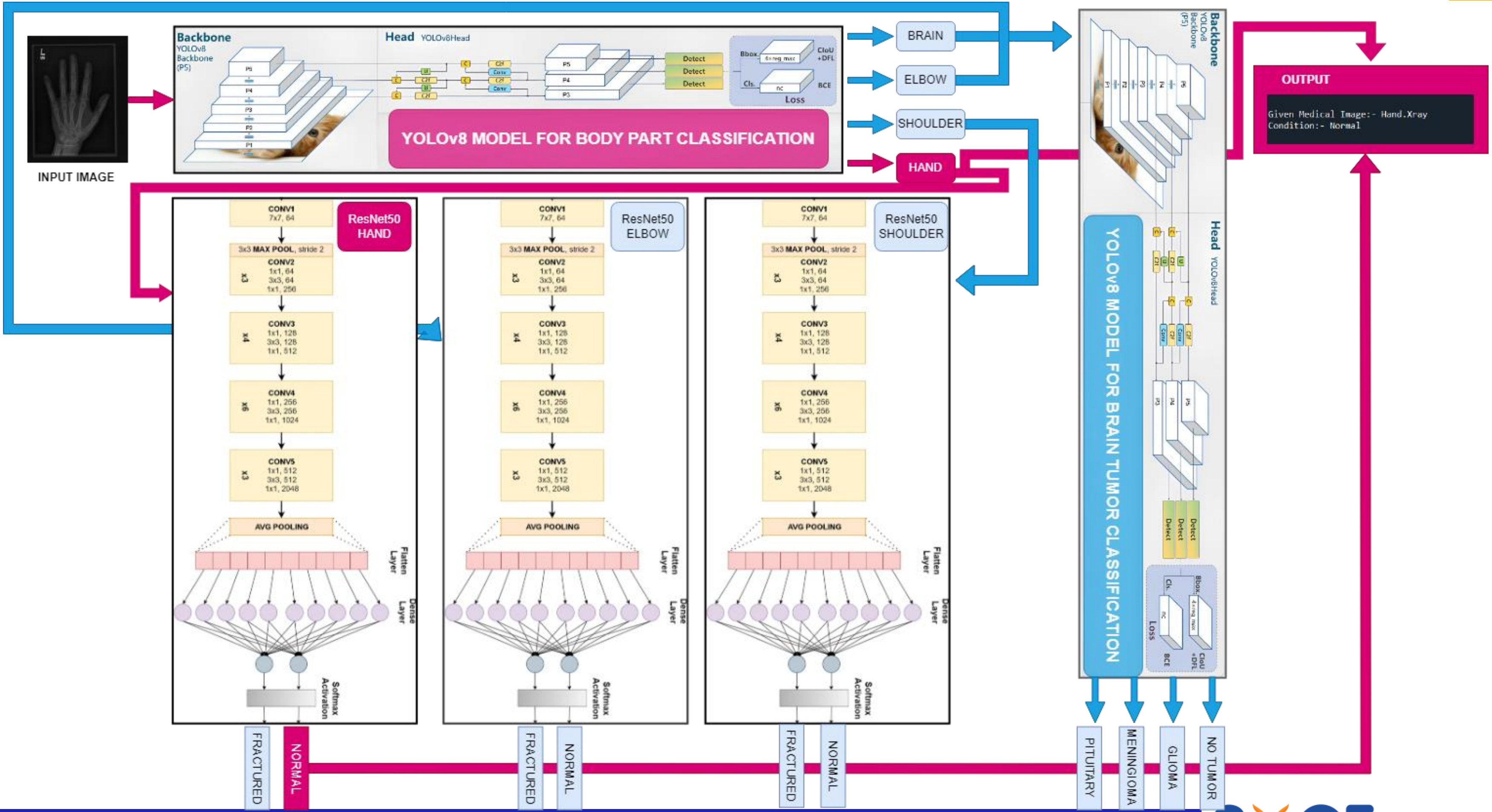
- Handling multi-modal medical images involves challenges with unwanted frames and the need to enhance accuracy rates. Varied resolutions, diverse anatomical structures, and potential overlaps demand sophisticated algorithms for precise classification in the presence of these complexities.

- Coordinating the diagnostic predictions poses challenges in aligning the results from the ResNet and YOLOv8 models with the appropriate treatment options, ensuring seamless integration into the healthcare system.

PROPOSED WORK

- Conducting thorough data cleaning and preprocessing, addressing flaw images, and ensuring data readiness for analysis.
- Stratifying the dataset into training, validation, and testing sets to facilitate the development and evaluation of the proposed multi-modal medical image classification and detection system.
- Constructing distinct ResNet models for the classification of X-ray images related to elbow, hand, and shoulder. Tailoring each model to predict specific medical conditions, which includes determining bone fractures accurately.
- Fine-tuning the YOLOv8 models for brain MRI tumor classification, distinguishing between glioma, meningioma, pituitary, and no tumor cases. Incorporating advanced image analysis techniques to enhance the accuracy of tumor classification. YOLOv8 and ResNet50 models utilize CNN as their backbone architectures.
- Implementing the YOLOv8 architecture for the classification of medical images, distinguishing between brain MRI, elbow X-ray, hand X-ray, and shoulder X-ray. Ensuring seamless routing of images to the relevant specialized models for accurate diagnosis.
- Ensuring the overall system optimization and integration into existing healthcare frameworks, facilitating a seamless and efficient diagnostic process for improved patient care.

ARCHITECTURE DIAGRAM



SYSTEM REQUIREMENTS AND TOOLS

HARDWARE COMPONENTS:

- CPU – Intel i7 13th gen
- 24 GB RAM
- 6 GB VRAM
- 1 TB SSD
- Windows 10 (64-bit)

SOFTWARE COMPONENTS:

- Python
- Deep Learning Framework
- IDE: Visual studio code

MODULES

- **Data Extraction & Preprocessing**
- **Building DNN Models**
- **Training Phase**
- **Testing Phase**

DATA EXTRACTION & PREPROCESSING

- **Data Extraction**:-This crucial phase initiates with the acquisition of high-quality medical image datasets from Kaggle. Specifically, for X-ray images of the hand, elbow, and shoulder, the MURA dataset is employed, encompassing approximately 20,000 images. Simultaneously, brain MRI images are sourced from Kaggle, constituting a dataset of around 7,000 images. The latter dataset is further categorized into glioma, meningioma, pituitary, and no tumor classes.
- **Data Preprocessing**: -During preprocessing, meticulous attention is given to standardizing image resolutions, addressing potential variations in anatomical structures, and ensuring uniformity across the diverse datasets. The preprocessing steps involve image normalization and resizing techniques to enhance the robustness of the dataset.
- **Data Splitting**:- For X-ray images (hand, elbow, shoulder), a prudent division is applied, allocating 72% of the dataset for training purposes. The remaining 28% is seamlessly distributed for testing and validation. In parallel, the Brain MRI dataset adopts an 81% training split, with the remaining 19% dedicated to testing and validation. This strategic allocation ensures a robust training regimen for model development while maintaining a substantial portion for thorough testing and validation, crucial for evaluating model performance and generalization.

BUILDING DNN MODELS

YOLOv8 Model for Body Part Classification:

- The YOLOv8 model is designed for object detection and classification tasks, and in this case, it will be used to classify whether an image is a brain MRI, hand X-ray, elbow X-ray, or shoulder X-ray.
- YOLOv8 employs anchor-free detection, predicting the center of an object directly without relying on anchor boxes.
- This reduces the number of box predictions, speeding up post-processing steps like Non-Maximum Suppression (NMS).
- The model includes changes in convolutional layers, such as replacing the first 6x6 convolution with a 3x3 convolution.
- The architecture incorporates a module known as C2f, which concatenates outputs from the bottleneck, influencing the model's efficiency.

BUILDING DNN MODELS

ResNet50 Models for Bone X-ray Condition Classification:

- ResNet50 utilizes deep residual learning to train much deeper models.
- It introduces skip connections, enabling the network to capture temporal dependencies more effectively.
- The model employs bottleneck blocks, consisting of 1x1 and 3x3 convolutions.
- Skip connections in these blocks facilitate the flow of information through the network.
- The models end with a dense layer, often with a softmax activation function for multi-class classification.

YOLOv8 Model for Brain MRI Tumor Classification:

- Another YOLOv8 model is constructed specifically for brain MRI images to classify and detect tumors (glioma, meningioma, pituitary tumors, or no tumor).
- Similar to the previous YOLOv8 model, it follows anchor-free detection and incorporates new convolutions. Additionally, it's trained to detect specific tumor classes.
- In both YOLOv8 models, activation functions, convolutional layers, and the overall architecture contribute to their ability to classify and detect objects efficiently.

TRAINING PHASE

- Load labeled dataset for brain MRI, hand X-ray, elbow X-ray, and shoulder X-ray images.
- Preprocess images: resize and normalize images for enhanced model generalization.
- Initialize YOLOv8 for body part classification and tumor classification, and ResNet50 for bone X-ray classification
- Choose loss functions: Varifocal loss for YOLO classification & detection, categorical cross-entropy for ResNet50 classification.
- Select optimization algorithm (e.g., Adam, SGD), tune hyperparameters, and train models iteratively.
- Iterate through the training dataset, passing batches of images through the respective models.
- Update model parameters using backpropagation and the chosen optimization algorithm.
- Monitor training metrics, such as loss and accuracy, to assess model performance during training.

TESTING PHASE

- The trained model, along with the loaded weights is saved, and the final phase involves displaying both actual and predicted results.
- Validate models periodically, fine-tune hyperparameters, and ensure satisfactory performance on both training and validation sets.
- Evaluate model predictions using appropriate metrics: accuracy, precision, recall, and F1 score.
- Analyze and visualize model outputs, identifying any misclassifications or false positives/negatives.
- Fine-tune models if needed based on test set performance, adjusting parameters for better generalization.
- Report final model performance, ensuring robustness across different image types and accurate predictions.

IMPLEMENTATION

DATA EXTRACTION & PREPROCESSING:

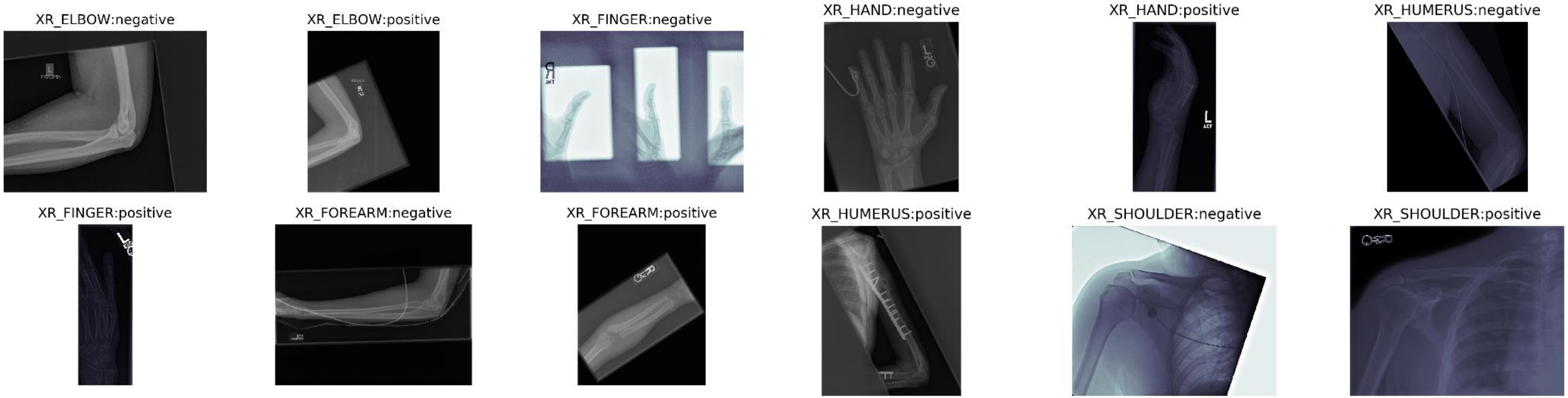


Fig 10.1 – SAMPLE IMAGES OF BONE FRACTURE DATASET

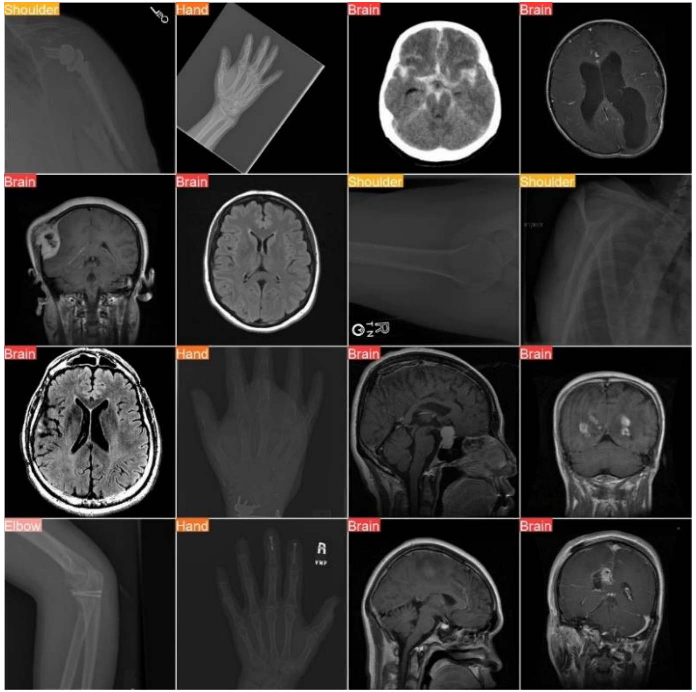
IMPLEMENTATION

DATA EXTRACTION & PREPROCESSING:

Fig 10.2 – SAMPLE IMAGES OF BRAIN MRI DATASET

IMPLEMENTATION

TRAINING AND VALIDATION:



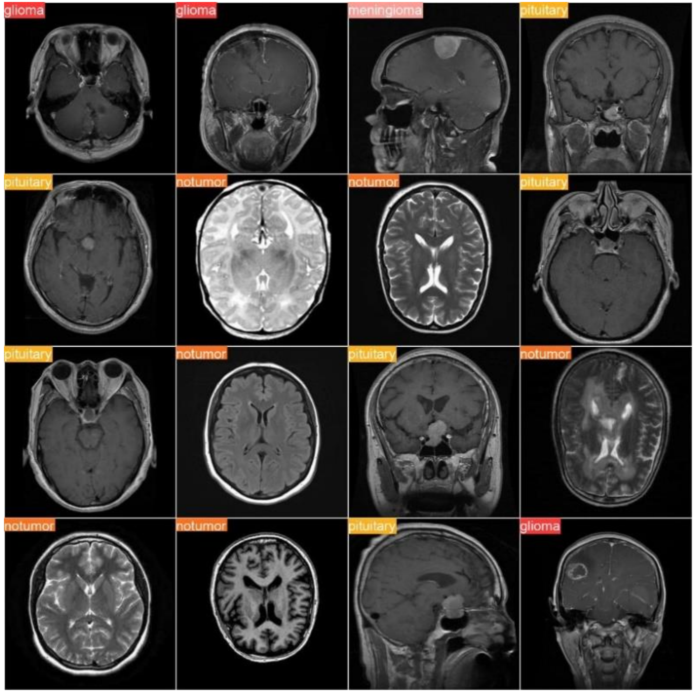
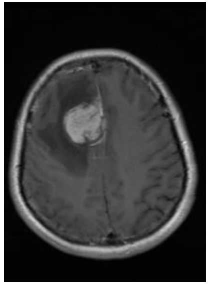


Fig 10.3 – SCREENSHOTS OF TRAINING AND VALIDATION PROCESS

IMPLEMENTATION

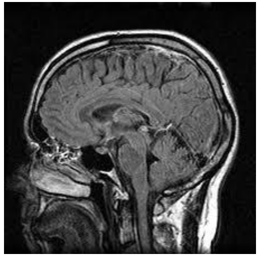
PREDICTIONS:


```
Given Medical Image:- Hand.Xray
Condition:- Normal
```



```
Given Medical Image:- Brain.MRI
Condition:- Tumor Detected
Type of Tumor:- Meningioma
```


```
Given Medical Image:- Elbow.Xray
Condition:- Fractured
```



```
Given Medical Image:- Brain.MRI
Condition:- No Tumor Detected
```

Fig 10.4 – OUTPUT SCREENSHOTS

IMPLEMENTATION

RESULT GRAPHS & PLOTS:

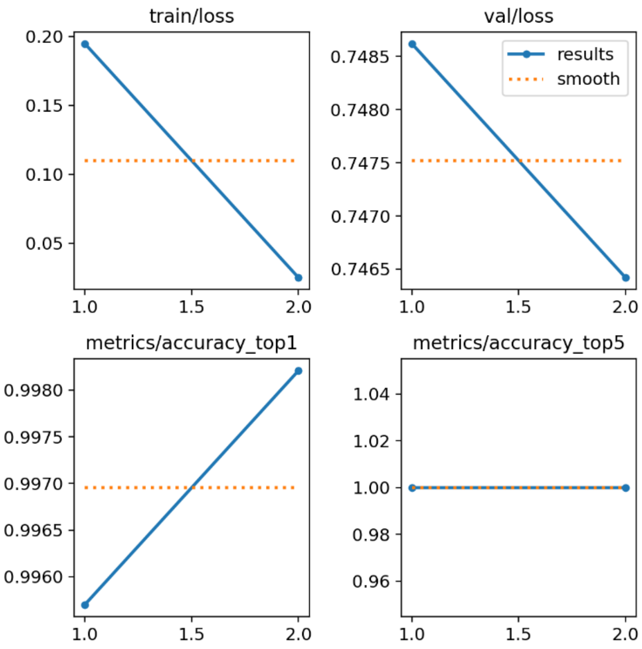


Fig 10.5 – ACCURACY GRAPHS OF BODY PART CLASSIFICATION

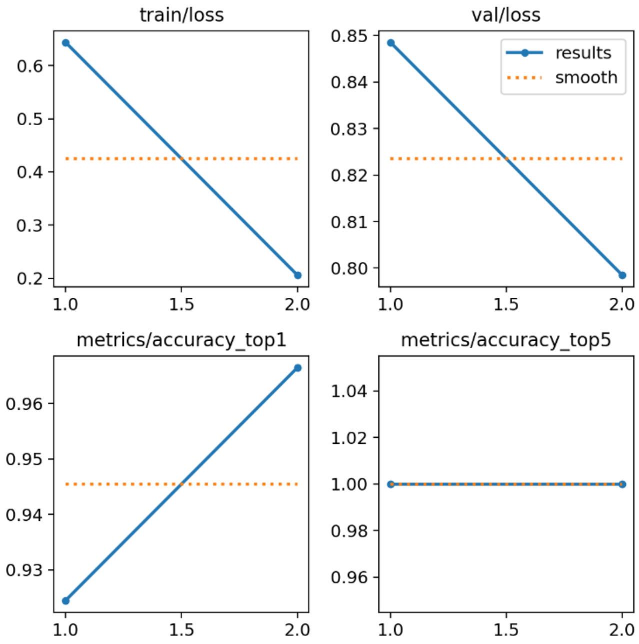


Fig 10.6 – ACCURACY GRAPHS OF BRAIN TUMOR CLASSIFICATION

IMPLEMENTATION

RESULT GRAPHS & PLOTS:

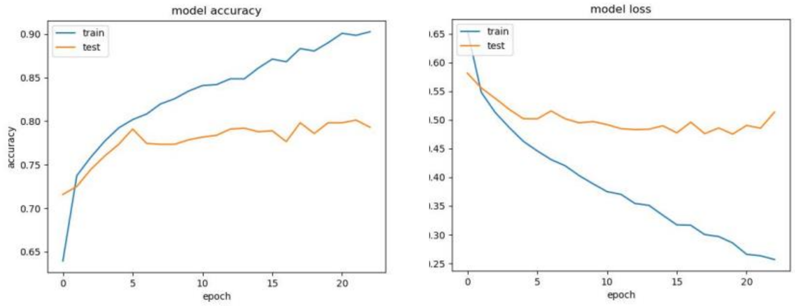


Fig 10.7 – ACCURACY GRAPHS OF ELBOW FRACTURE CLASSIFICATION

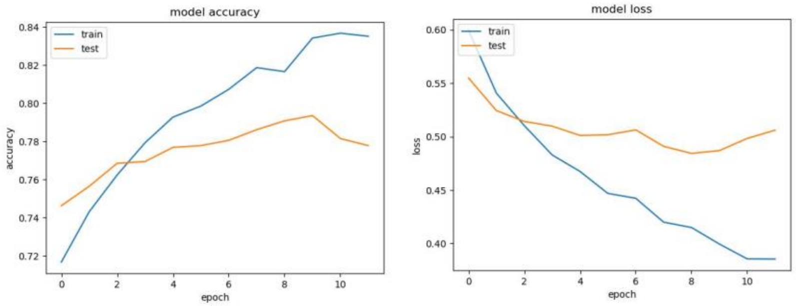


Fig 10.8 – ACCURACY GRAPHS OF HAND FRACTURE CLASSIFICATION

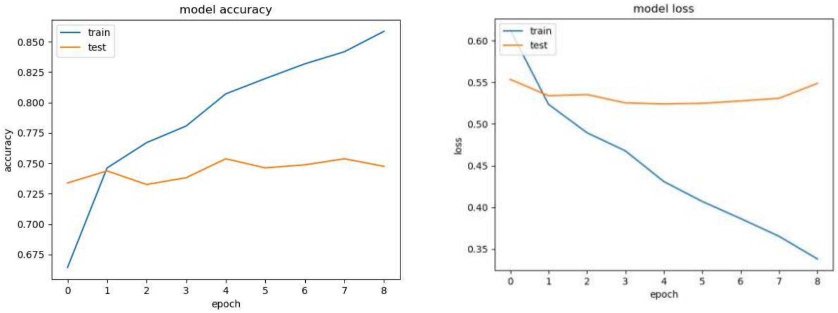


Fig 10.9 – ACCURACY GRAPHS OF SHOULDER FRACTURE CLASSIFICATION

IMPLEMENTATION

CONFUSION MATRIX:

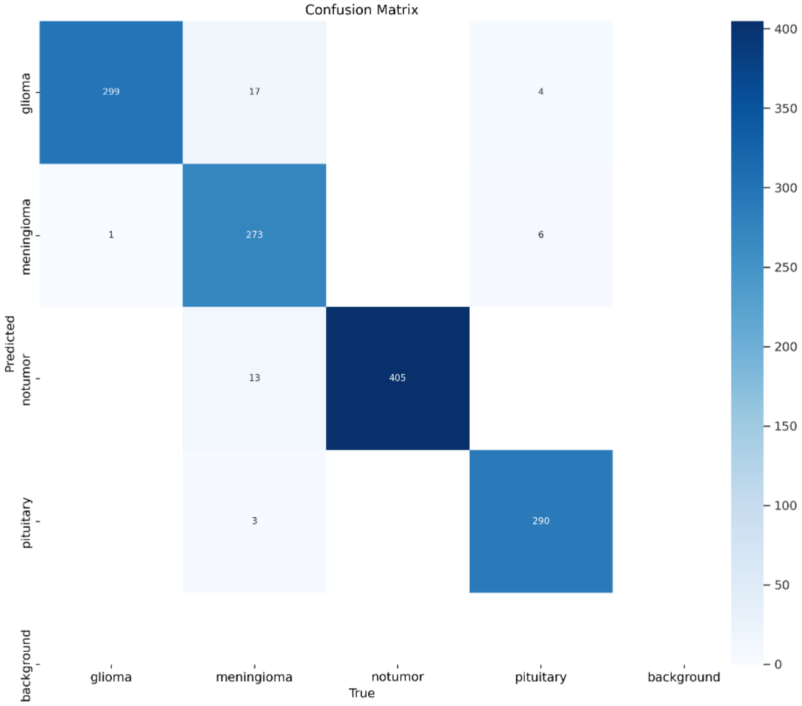


Fig 10.10 – CONFUSION MATRIX OF BRAIN TUMOR CLASSIFICATION

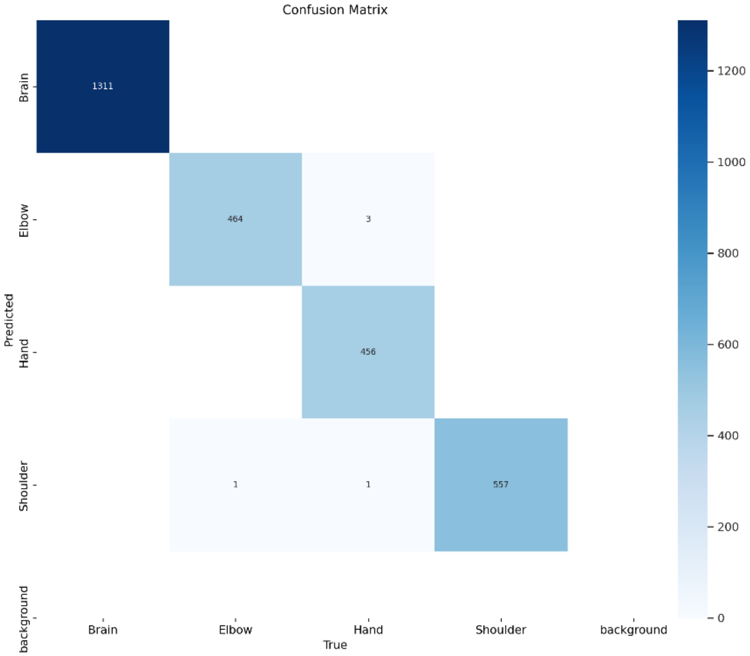


Fig 10.11 – CONFUSION MATRIX OF BODY PART CLASSIFICATION

REFERENCES

- Z. Atha and J. Chaki. (2023), “SSBTCNet: Semi-Supervised Brain Tumor Classification Network”, IEEE Access, Vol. 11, pp. 141485-141499.
- F. Mohammad, S. Al-Ahmadi and J. Al-Muhtadi, (2023), “Block-Deep: A Hybrid Secure Data Storage and Diagnosis Model for Bone Fracture Identification of Athlete From X-Ray and MRI Images”, IEEE Access, Vol. 11, pp. 142360-142370.
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- R. Zaitoon and H. Syed, (2023). “RU-Net2+: A Deep Learning Algorithm for Accurate Brain Tumor Segmentation and Survival Rate Prediction”, IEEE Access, Vol. 11, pp. 118105-118123.

THANK YOU