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Develop an Extended Model of CNN Algorithm in Deep Learning for Bone Tumor Detection and its Application

(Area of Focus: Deep Learning)

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Abstract:- Deep leaning in orthopedic surgery has gained mass interest over the last decade or so. In prior studies, researchers have demonstrated that deep learning in orthopedics can be used for different applications such as fracture detection, bone tumor diagnosis, detecting hip implant mechanical loosening, and grading osteoarthritis. As time goes on, the utility of deep learning algorithms, continues to grow and expand in orthopedic surgery. The purpose of this research was to develop an extended model of CNN algorithm in deep learning for bone tumor detection and its application. Bone tumors can be malignant growths. Despite the fact that it can happen in any bone, it frequently happens in long bones like the arms and legs. Although the exact source of this malignant tumor is yet unknown, doctors believe that DNA abnormalities within the bones are to blame. In addition to destroying good bodily tissue, this results in immature, crooked, and diseased bone. When a bone tumor is suspected, the first test is a bone X-ray. The greatest method for detecting cancer in the bones is through imaging and X-ray scans. The recommended procedure that can provide a certain diagnosis is a biopsy. This labor-intensive and challenging process can be mechanized. We presented a number of supervised deep learning techniques and chose the suitable model. To find bone cancer, a selection is made using the weighted average of user data. Using the residual neural network (ResNet101) technique, we extended the models that were chosen and they met the expectations with the maximum accuracy (90.36%) and precision (89.51%), respectively, for the prediction tasks.

Keywords:- *CNN: Convolutional Neural Networks, ANN: Artificial Neural Networks, MRI: Magnetic Resonance Imaging, AI: Artificial Intelligence.*

I. INTRODUCTION

Certainly, deep learning has emerged as a promising technology for medical imaging analysis, including the detection and diagnosis of bone tumors. Traditional machine learning methods rely on expert input to extract features relevant to identifying bone tumors in medical images, but deep learning algorithms can learn these features on their own from raw data. This is especially useful in medical imaging where there is a vast amount of data to be analyzed. The use of convolutional neural networks (CNNs) has led to highly accurate and efficient classification of different types of tumors based on medical images such as X-rays, CT scans, and MRI. As bone tumors can be difficult to distinguish from normal bone tissue, the accuracy and efficiency provided by deep learning algorithms can significantly improve early diagnosis and treatment of bone tumors. Overall, deep learning has the potential to transform the field of medical imaging analysis and improve patient outcomes.

II. METHODOLOGY

- *Data Collection Methods and Instruments/ Tools*

The practice of gathering information using specified procedures in order to react to the study's predetermined research subject is known as data collecting. In this study, the researcher used mixed method (both qualitative and quantitative) and examined secondary data.

- *Data Analysis*

The process of discovering solutions through investigation and interpretation is known as data analysis. Understanding survey and administrative source results and presenting data information require data analysis. Data analysis is anticipated to provide light on the subject of the study and the respondents' perceptions, as well as to increase readers' understanding of the subject and pique their interest in this portion of the research. Jupyter notebook was used to analyze the data and present the results by measuring the **performance metrics**.

- *Research Design*

A research design is a plan or blueprint which shows how data required for the solution of the problem that the researcher focused on, the procedure and methods for data collection and analysis, answered the research questions. In these lines the research herein the present study, researcher would employ a combination of descriptive and correlation research design to describe the characteristics of a population under investigation and carefully examine the use CCN algorithm in bone tumor detection (Hardt,2016).

- *Objective:*

The objective of this study is to develop an extended model of a Convolutional Neural Network (CNN) algorithm for bone tumor detection. Additionally, the study aims to explore the practical application of the developed model in real-world scenarios.

- *Data Collection:*

Gather a comprehensive dataset of medical images that includes various types of bone tumors and normal bone images. Ensure that the dataset represents a diverse range of cases, including different tumor types, sizes, and locations. Collect the data from medical archives, hospitals, or curated datasets.

- *Data Preprocessing:*

Preprocess the collected medical images to enhance their quality and enable compatibility with deep learning algorithms. Apply techniques such as resizing, cropping, normalization, and noise removal to ensure consistent image quality throughout the dataset.

- *Splitting the Dataset:*

Divide the dataset into training, validation, and testing subsets. Use an appropriate split, such as 80% for training, 10% for validation, and 10% for testing. This split allows training the model, optimizing hyper-parameters, and evaluating the performance effectively.

- *Model Architecture:*

Design an extended CNN architecture that builds upon existing CNN models for bone tumor detection. Consider incorporating additional layers, such as residual connections, attention mechanisms, or novel convolutional filters, to enhance the model's performance. Experiment with different architecture modifications to find the best approach.

- *Training the Model:*

Train the extended CNN model using the training dataset. Utilize loss functions like categorical cross-entropy or focal loss, and optimizer algorithms such as Adam or RMSprop. Implement appropriate techniques like data augmentation to augment the training dataset and increase its diversity.

- *Model Evaluation:*

Evaluate the trained model using the validation dataset. Monitor performance metrics such as accuracy, precision, recall, F1 score, and area under the ROC curve. Conduct multiple epochs of training and validation to fine-tune the model's hyperparameters and ensure optimal performance.

- *Testing and Application:*

Test the final trained model using the independent testing dataset to assess its performance on unseen data. Evaluate metrics like accuracy, sensitivity, specificity, and area under the ROC curve on the test dataset. Additionally, deploy the model in real-world scenarios, such as using it in a software application or a medical imaging system, to demonstrate its practical application.

- *Ethical Considerations:*

Address ethical considerations such as data privacy, patient consent, and responsible use of AI in healthcare. Ensure compliance with ethical guidelines and regulations throughout data collection, model deployment, and dissemination of research findings.

➢ *CNN (Convolutional neural networks)*

CNN are a specific type of neural network designed for processing data that possesses a grid-like structure. Examples of such data include time series data, which is regarded as a 1D grid with regularly spaced samples over time, and image data, which is treated as a 2D grid composed of pixels. CNNs have demonstrated remarkable effectiveness in practical applications. The term "convolutional neural network" refers to the network's utilization of the mathematical operation called convolution. Convolution belongs to the broader category of linear operations. Convolutional networks can be viewed as neural networks that incorporate at least one layer where convolution operations are employed instead of general matrix multiplication (LeCun, 1989).

➢ *Methodology for Bone Tumor Detection using Convolutional Neural Network Models*

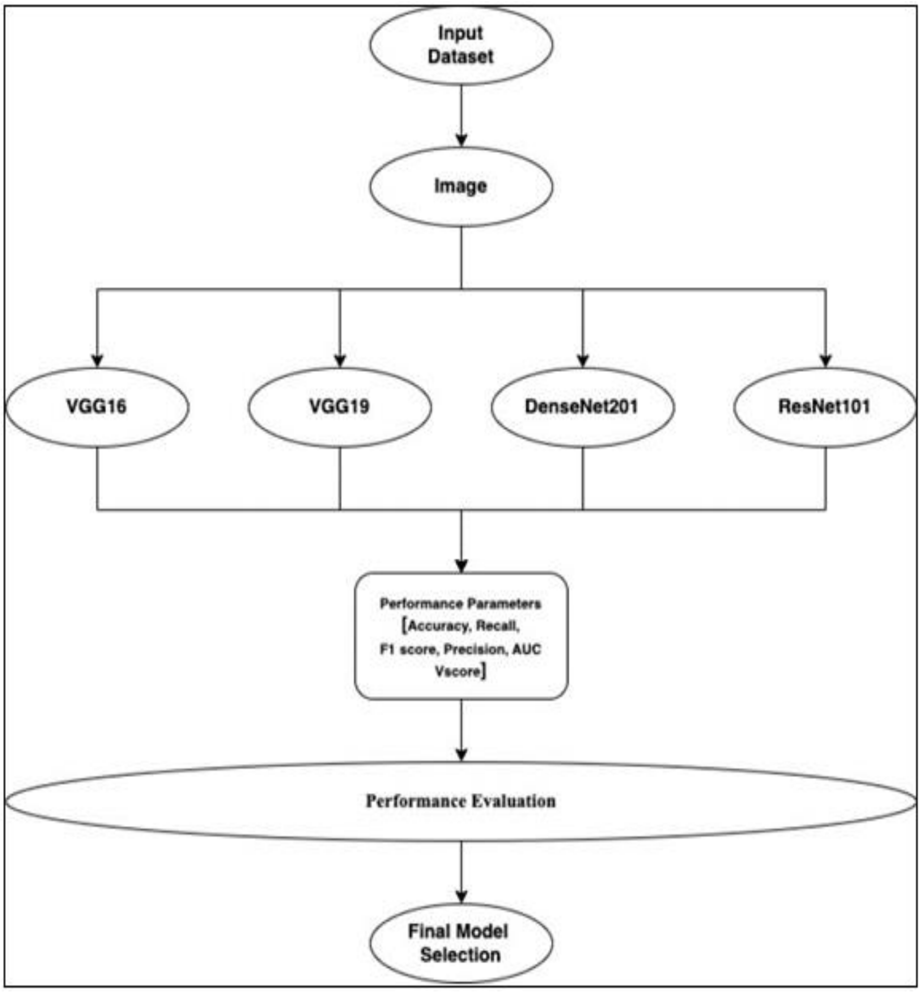

Fig 1 Methodology for Bone Tumor Detection using CNN Models

➢ *VGG16 (Visual Geometry Group 16)*

The VGG-16 model is a convolutional neural network (CNN) consisting of 16 layers. It is widely recognized as one of the top-performing and efficient models available today. In contrast to architectures with different params, VGG16 model relies on Convolutional Network layers using a 3x3 size of the kernel. This model is particularly valuable because it can be found and downloaded online for various systems and applications. Its simplicity stands out compared to other comprehensive models that have been developed.

For the VGG-16 model, the minimum input image size required is 224x224 pixels with three channels. In neural networks, optimization techniques are employed to assess the involvement of a neuron by calculating the weighted sum of its inputs. A kernel function is utilized to introduce non-linearity in the output neuron. Neurons in a neural network interact with weights, biases, and training techniques. The connection weights between neurons are adjusted based on the desired output. Input images and activation functions play a significant role in introducing nonlinearity into artificial neural networks.

➢ *Ethical Considerations*

The data collected for this study is protected with the help of ethical consideration. Research ethics is the obligation of researchers to be truthful and considerate to everyone who is impacted by their study or the results report. Several ethical rules are typically applied to researchers.

- *Data Privacy and Security:*

Ensure that patient privacy is protected throughout the data collection, handling, and storage process. Follow data protection regulations and guidelines, such as anonymizing or de-identifying patient information, encrypting sensitive data, and implementing secure data storage practices.

- *Informed Consent:*

Obtain informed consent from patients or individuals whose medical images are included in the dataset. Ensure that participants understand the purpose of the study, how their data will be used, potential ramifications, and their rights regarding data handling and privacy.

- *Bias and Fairness:*

Be aware of potential bias during data collection and model development stages. Take measures to address and mitigate biases in the dataset, such as ensuring diverse representation of demographics and accounting for potential disparities in disease prevalence across different populations. Regularly evaluate the model's performance across various subgroups to ensure fairness and avoid discrimination.

- *Transparency and Explainability:*
  Strive for transparency in the development and implementation of the deep learning model. Clearly document the methodology, architecture, and any modifications made to the CNN algorithm. Consider incorporating interpretability techniques to provide explanations for the model's decisions, enabling healthcare professionals to understand and trust the model's output.

- *Ethical use of AI:*
  Ensure that the developed model is used ethically and responsibly. Consider potential risks, limitations, and implications of the model's application in real-world scenarios. Monitor and address any unintended consequences that may arise from using the model, and regularly update and improve the model as needed.

- *Continual Evaluation and Validation:*
  Regularly assess and validate the performance of the extended CNN model, both during development and after deployment. Maintain ongoing monitoring of the model's accuracy, reliability, and generalizability. Address any performance issues, biases, or unintended consequences that may emerge.

- *Collaboration and Collaboration with Medical Professionals:*
  Collaborate closely with medical professionals, radiologists, and other healthcare practitioners throughout the research and development process. Seek their expertise, guidance, and feedback to ensure the model aligns with clinical needs, enhances patient care, and adheres to ethical standards.

- *Responsible Reporting and Dissemination:*
  Accurately report and transparently share the findings of the research study, including any limitations or challenges encountered during the development of the extended CNN model. Avoid sensationalism or overstatements about the model's capabilities. Share the research findings within the scientific community, enabling peer review, replication, and further advancements in the field.

These ethical considerations are crucial to ensure patient safety, privacy, and fairness while promoting responsible development of an extended model of CNN algorithm in deep learning for bone tumor detection and its application in the healthcare domain.

➢ *Applied Algorithms to Extend CNN Models*

- **VGG16:** Convolutional Neural Network (CNN) architecture Visual Geometry Group-16 concentrates on having convolution layers of 3 × 3 filter with a stride 1 and always uses the same padding and maxpool layer of 2 × 2 filter with stride 2. It is 16-layer Convolutional Neural Network architecture; the “16” in VGG16 denotes that it includes 16 layers with weights.
- **VGG19:** is a Convolutional Neural Network architecture which is widely used for image classification and other applications that has been trained on the Image dataset It was created at Oxford University by the Visual Geometry Group and is distinguished by the use of extremely tiny (3 × 3) and deep (3 × 3) convolutional filters (19 layers). The architecture is straightforward yet effective and has served as the foundation for several cutting-edge models.
- **DenseNet201:** A convolutional neural network architecture called DenseNet201 is a development on the DenseNet framework. It was created in 2017 by Gao Huang and colleagues. The primary concept of DenseNet is to feed-forward link each layer to every other layer. As a result, a dense connectivity network is produced, which enhances feature reuse and lessens the issue of disappearing gradients. A DenseNet architecture variant called DenseNet201 contains 201 layers. It is frequently used in computer vision applications like object identification and picture categorization.
- **ResNet 101:** Convolutional Neural Network architecture, in 2015. The ResNet model, which stands for “Residual Network”, is a version of this one. The introduction of “residual connections”, which enable the network to study residual functions with relevance to the layer inputs instead of learning unsourced functions, is the main novelty of ResNet. As a result, training very deep networks (152 layers or more) is now feasible without experiencing diminishing gradient issues. A ResNet variant with 101 layers is known as ResNet101. It has broken previous records for image classification performance on the ImageNet dataset and is frequently used for image classification and object recognition applications

➢ *Data Analysis and Presentation of Findings*

Performance metrics were used as a data analysis technique in this study, and the produced graphs were examined. Data were loaded and split with split sizes of 0.8 and 0.2 into training and testing groups. The GPU Tesla T4 with an image size of [256,256] was used, and the batch size was set at 64. 'VGG16', 'VGG19', 'DenseNet201', and 'ResNet101' ImageNet models were used for classification, with the output layer set to softmax activation function. 'Non-Tumor,' 'Non-Viable-Tumor,' and 'Viable-Tumor' were the three groups into which the photos in the dataset were split. Adam optimizer and tf.keras.losses were employed. AS a loss function, categorical Cross-entropy was used.

III. DATA PRESENTATION

➢ *Validation Accuracy Curve for all Models*

The figure below represented the accuracy achieved by all the models, acceptable and shows the Validation Accuracy of all Models '**VGG16'**, **'VGG19'**, **'DenseNet201'**, and **'ResNet101'**.

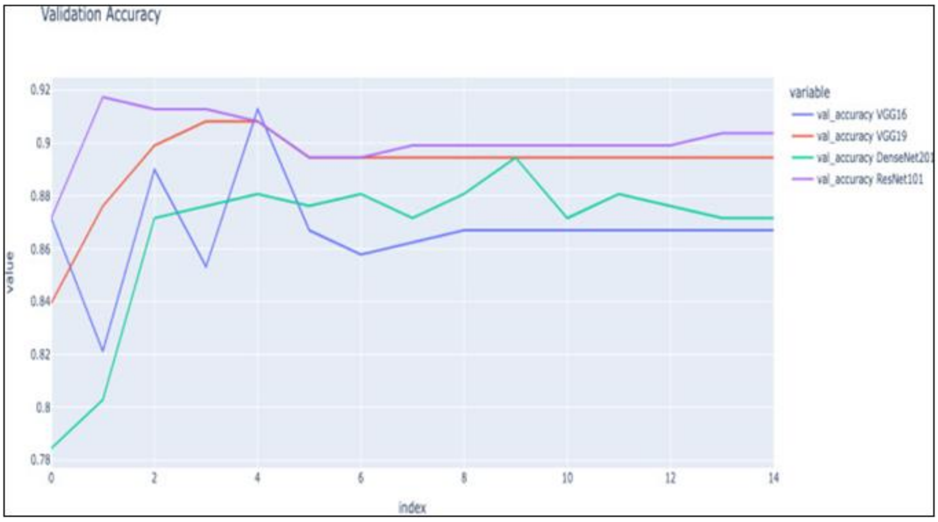

Fig 2 Validation Accuracy Curve for all Models

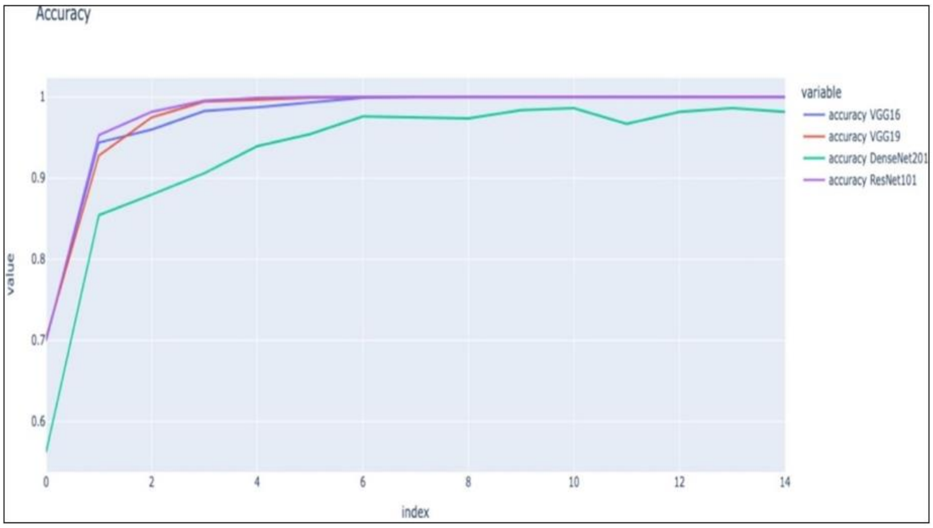

Fig 3 Accuracy of all Models

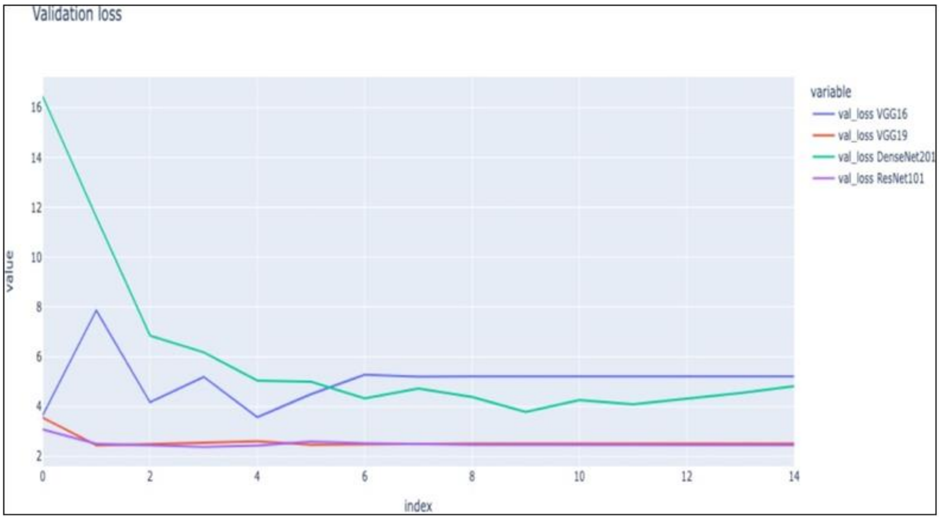

Fig 4 Validation Loss curve for all models

- *Comparative Interpretation of Findings between VGG16,VGG19,DenseNet201 and ResNet101 Models*

Table 1 Performance of Algorithms Performed on the Dataset

Parameters	VGG16	VGG19	DenseNet201	ResNet101
Accuracy	86.69%	89.44%	87.15%	90.36%
F1	85.50%	88.33%	85.50%	89.35%
Precision	84.31%	87.79%	84.38%	89.51%
Recall	87.21%	88.94%	87.15%	89.59%
AUC	0.909	0.931	0.909	0.946
Vscore	2.361	2.506	1.970	2.720
Comments		Here **VGG16** in the result About the accuracy on the highest		**ResNet101** is the best Predict the bone tumor Compare to other models

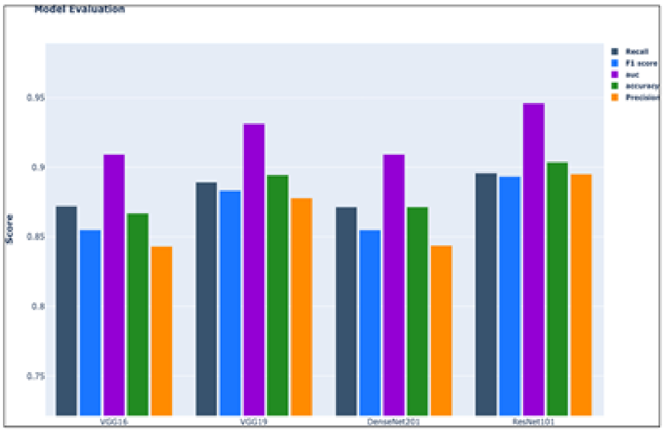

Fig 5 Evaluation of Algorithms Performed on the Dataset

- *Confusion Matrix of Models*

To find misclassifications, compares a classification model's predicted and actual values. The confusion matrix helped me in the performance optimization of my models. The figures below show the visualization of the performance on the models. TensorFlow was utilized to build these classification models.

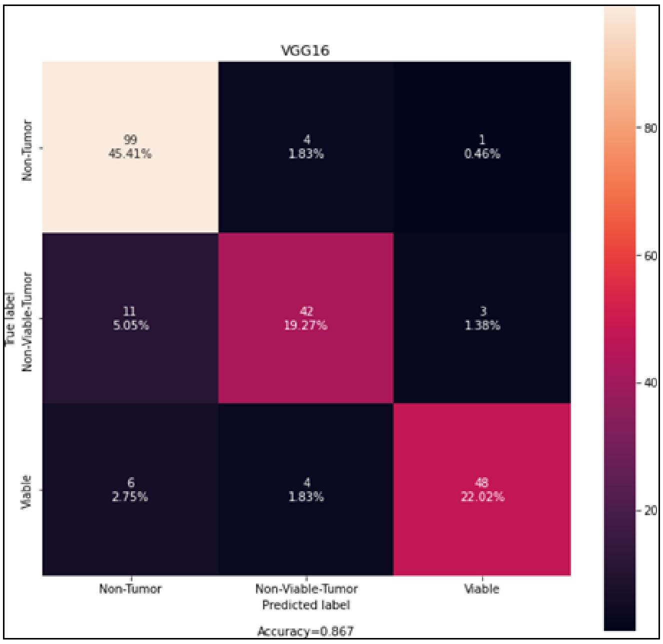

Fig 6 Confusion Matrix for VGG16

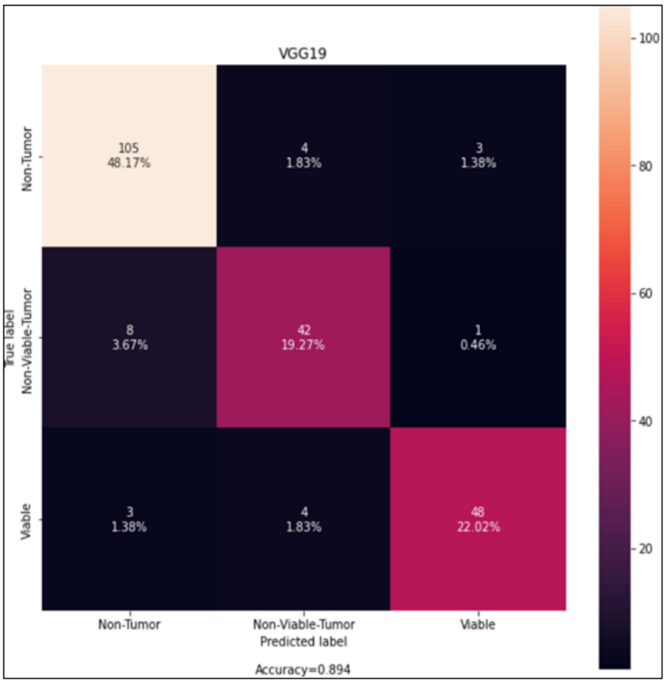

Fig 7 Confusion Matrix for VGG19

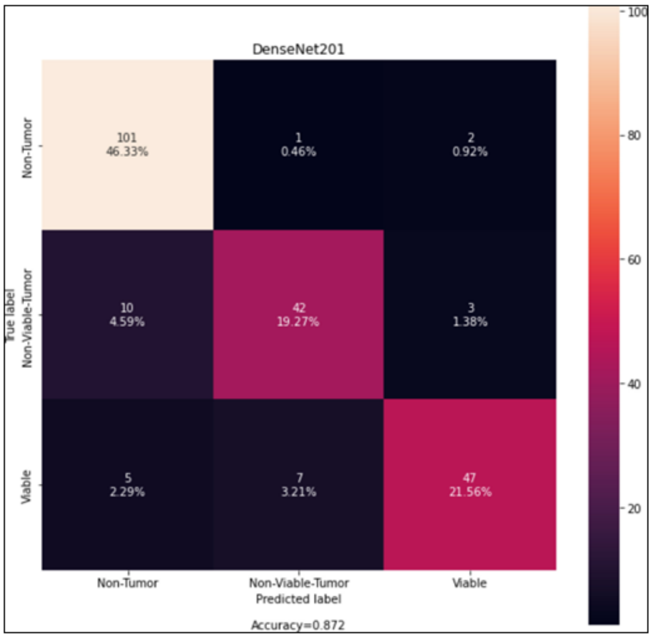

Fig 8 Confusion Matrix for DenseNet201

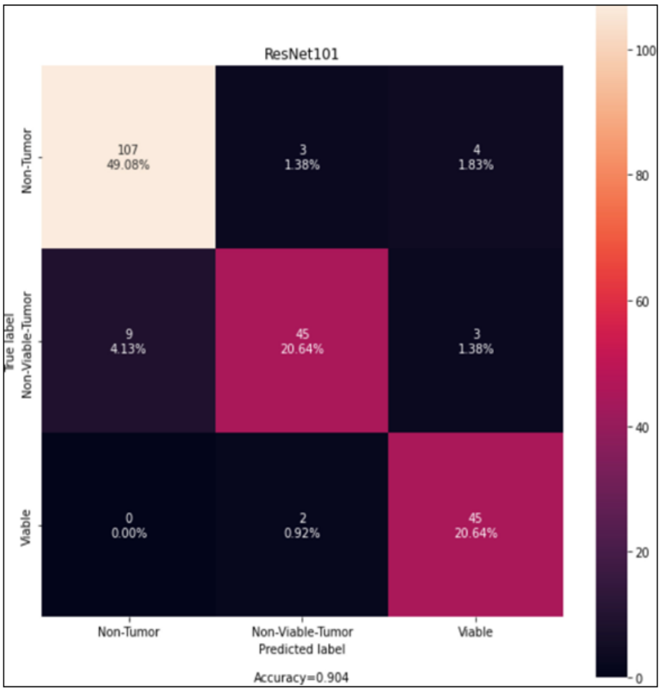

Fig 9 Confusion Matrix for DenseNet101

➢ *Model Evaluation*

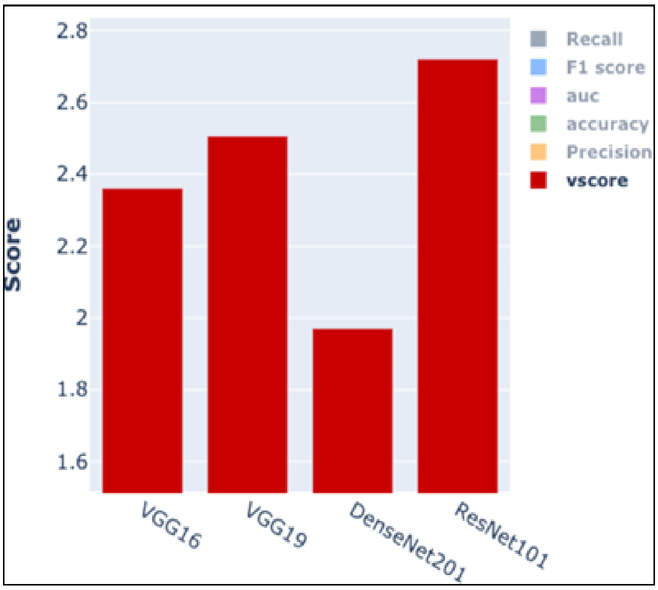

Fig 10 Comparative of V-Score for all Models

IV. CONCLUSIONS AND DISCUSSIONS ON THE FINDINGS

For the formation of model, the proposed framework is composed to use supervised deep learning methods. And, for classification problem VGG16, VGG19, DenseNet201 and ResNet101 algorithms were applied. The VGG16 model has an accuracy of 86.69%, an F1-score of 85.5%, an AUC of 0.909, a precision of 84.31%, a recall of 87.21%, and vscore of 2.36 which fared average as compared to other models. The VGG19 model has an accuracy of 88.94%, an F1-score of 88.33%, an AUC of 0.9314, a precision of 87.79%, a recall of 88.94%, and vscore of 2.506 which is the second-best score as compared to other models, here we can see that ResNet101 Convolutional Neural Network architecture was better suited for the detection bone tumor

The DenseNet201 model has an accuracy of 87.15%, an F1-score of 85.5%, an AUC of 0.9093, a precision of 84.38%, a recall of 87.15%, and vscore of 1.907 which is the lowest amongst the tested models, the metrics are similar as VGG16 but the vscore is low because of time factor. The ResNet101 model has an accuracy of 90.36%, an F1-score of 89.35%, an AUC of 0.9461, a precision of 89.51%, a recall of 89.59%, and vscore of 2.72 which is the highest as compared to other models, the residual neural network (ResNet101) fared well as compared to other models and with lowest time take to train the model and highest accuracy.

Notably, it is essential to emphasize that the ResNet101 model outperformed the CNN model in terms of accuracy and F1 score. This implies that ResNet101 model delivered more precise results and achieved a better balance between precision and recall in the specific context of bone tumor detection.

In conclusion, after meticulously analyzing performance metrics, plotted graphs, and confusion matrices, I strongly recommend that Rwanda Military Hospital to deploy the ResNet101 Approach model for bone tumor detection. The ResNet101 model demonstrated exceptional accuracy and precision on the test set. By deploying this model, the hospital can ensure reliable and accurate bone tumor detection outcomes.

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