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Deep Learning based approach for identification of knee defects using Magnetic Resonance Imaging

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***Abstract*— Knee arthroscopy is a form of minimally invasive surgery (MIS) in which an arthroscope and a surgical tool is inserted into the knee through small incisions. Every year, about four million of these surgeries are done across the world, at a total cost to the global healthcare system of $15 billion USD. This study evaluates existing and innovative knee injury detection methods using Stanford's MRNet Dataset. All of the strategies are deep learning-based, and the outcomes of transfer learning and a deep residual network created from the ground up are contrasted. This paper also takes use of certain MRI data characteristics, such as employing a fixed number of slices or 2D images from each of the axial, coronal, and sagittal planes, as well as merging the three planes into a single multi-plane network. More adaptable designs are also shown, which may benefit in the development and training of MRI-processing models. The developed model achieved the average accuracies of 95%, 96%, and 89% for abnormal, ACL tear, and Meniscal tear respectively on the axial, coronal, and sagittal planes.**

Keywords*— *MRI, Knee-Injuries, Transfer learning, Deep Learning

I. Introduction

Knee arthroscopy is a type of minimally invasive surgery (MIS) that involves inserting an arthroscope and a surgical instrument into the knee through tiny incisions. More than four million of these operations are performed worldwide each year, at a total cost to the global healthcare system of $15 billion USD[1]. The sophisticated surgical approach has the potential to produce unexpected femoral cartilage injury as well as additional postoperative problems such as hemarthrosis. Robotics and medical imaging advancements have the potential to eliminate these surgical restrictions and increase the accuracy, stability, and precision of knee surgery operating procedures. Following an initial phase in which an improved image of the intraarticular knee anatomy is created, it is conceivable to imagine the development of stand-alone robotic assistance instruments to automate the whole surgical operation and, ultimately, improve patient outcomes.

In this work, we use deep learning algorithms to automatically assess whether a patient has a ligament rupture using the MRNet dataset, a publicly available collection of knee MRI images. Some are well-known and well-described, while others are brand-new and presented here for the first time. The rest of this paper explains how we employed several deep learning algorithms on this dataset. At the time of writing, our findings were best-in-class, and the essay explains why our algorithms perform so well on this sort of classification challenge. The following are the important lessons to remember:

i) In this section, the recommended methodologies will be described in depth, and the quantitative and qualitative experimental findings will be presented.

ii) Too much or too little data augmentation can be harmful to performance, but a correctly calibrated augmentation policy can provide significant performance improvements.

iii) Using VGG-Net, we calculate accuracy on all three planes (Axial, Coronal, and Sagittal).

II. Literature Review

David Azcone, et al. (2020): Using Stanford's MRNet knowledge unit, this research compares and contrasts existing and novel strategies for detecting knee injuries. All of our points of view are based on deep learning, and They compare the results of transfer learning with a deep residual network developed from the ground up. They also improve several MRI data properties by, for example, employing a predetermined number of thin, broad bits or 2d pictures from each of the axial, coronal, and sagittal planes, as well as integrating the three planes into one multi-plane network. Overall, utilising the most recent deep learning buildings and structure design and data method of producing more thoroughly researched designs, They produced a performance of 93.4% AUC on the say for specific data . More adaptable structures and buildings are now available, which may aid in the creation and training of MRI-processing models. They observed that transfer learning and a carefully adjusted data augmentation thoroughly crafted design were crucial in selecting the optimal way to execute a play[2].

Maria Antico, et al. (2020): Knee arthroscopy is a difficult minimally invasive procedure that might result in femoral cartilage damage, postoperative problems, or both. The imaging system should produce a real-time full picture of the surgical site to enable the robotic system to maneuver autonomously in the knee joint. With fivefold cross-validation, the system was assessed using the expert labels as ground truth, with each fold being trained and tested on average with 15 640 and 6246 tagged pictures, respectively. Between two experts (interobserver) and each expert (intraobserver), percent agreement values of 0.89 and 0.93 were reached, respectively. These findings demonstrate that the first crucial step in the development of automatic US image capture and interpretation systems for autonomous robotic knee arthroscopy is feasible[1].

Zhaoye Zhou, et al. (2018): To present and evaluate a novel knee joint tissue segmentation approach that uses a deep convolutional neural network (CNN), a 3D fully connected conditional random field (CRF), and 3D simplex deformable modelling to increase efficiency and accuracy. For segmenting all knee joint structures, the suggested segmentation approach performed well. The femur, tibia, muscle, and other unspecified tissues were among the four tissue categories with a high mean Dice coefficient over 0.9. Joint effusion and Baker's cyst were the only tissue types with a mean Dice coefficient between 0.7 and 0.8. The average symmetric surface distance of most musculoskeletal tissues was less than 1mm[3].

Artjoms Suponenkovs, et al. (2017): The challenge of automated knee-joint soft tissue detection is becoming increasingly important as the number of persons with knee-joint disorders rises. This work explores the difficulty of soft tissue identification in magnetic resonance imaging for this reason (MRI). Although MRI is effective for presenting soft tissue in the knee, it is rare for a clinician to be able to view all of the information needed in MRI data. Soft tissue identification and analysis in the knee joint are quite useful, especially in the early stages of osteoarthritis (OA). It permits therapy to begin sooner, reducing the risk of tissue damage. As a result, the above-mentioned issues are the focus of this study[4].

Alexander D.Orsi, et al. (2014): This work used a three-dimensional model of the knee joint to evaluate which knee joint motion schemes result in ACL injury, as well as to investigate the different forms of concurrent injuries associated with each motion scheme. The correlations between knee joint orientation and different tissue failures were investigated, and susceptibility spectrums for knee injuries were generated. The posterolateral bundle was shown to be more prone to rupture than the anteromedial bundle. The average varus angular displacement after ACL failure was 46.6 percent less than the average valgus angular displacement. Articular cartilage damage was observed prior to ACL collapse in all valgus scenarios[5].

Chen-Hen Tsai et al. (2020): For knee injury analysis, magnetic resonance imaging (MRI) is an extensively used imaging technique. Its ability to capture three-dimensional knee structure makes it a useful tool for radiologists looking for potential tears in the knee. Automated methods for patient triage are becoming a real need to better deal with the ever-increasing workload of musculoskeletal (MSK) radiologists, decreasing delays in the reading of pathological cases. The Efficiently-Layed Network (ELNet), a convolutional neural network (CNN) architecture optimized for early knee MRI diagnosis for triage, is presented in this paper. Unlike previous techniques, we train ELNet from the ground up rather than using a transfer-learning method. While using a single image stack (axial or coronal) as input, the suggested method is quantitatively and qualitatively validated and compares favorably to state-of-the-art MRNet. In addition, despite the lack of localization information during training, we show that our model can find tears in the knee. Finally, the suggested model is incredibly lightweight (less than 1MB), making it simple to train and use in real-world clinical situations[6].

Nicholas Bien et al. (2018): The preferred method for diagnosing knee injuries is magnetic resonance imaging (MRI). However, interpreting knee MRI takes time and is subject to diagnostic error and variability. An automated system for interpreting knee MRI could help clinicians prioritise high-risk patients and make diagnoses. Deep learning methods are well suited for modelling the complex relationships between medical images and their interpretations because they can automatically learn layers of features. In this study, we developed a deep learning model for detecting general abnormalities as well as specific diagnoses (ACL tears and meniscal tears) on knee MRI exams. We then assessed the impact of providing clinical experts with the model's predictions during interpretation. From the Clinical Hospital Centre Rijeka in Croatia, we also got a public dataset of 917 tests with sagittal T1-weighted series and classifications for ACL injury. We discovered no significant differences between the model's performance and that of unassisted general radiologists in detecting anomalies using a 2-sided Pearson's chi-squared test with multiple comparisons adjustment. The lack of surgical ground truth and the limited size of the panel of clinical experts are the study's principal shortcomings. From both internal and external datasets, our deep learning model can quickly generate correct clinical pathology classifications of knee MRI scans. Furthermore, our findings back up the claim that deep learning models can help clinical specialists perform better during medical imaging interpretation. More research is needed to prospectively validate the model and assess its value in the clinical context[7].

III. Problem Formulation

How to build a deep learning architecture to improve classification performance on a collection of MRI images of the knee is a common topic in the study. On the other hand, MRI interpretation of the knee takes time and is prone to diagnostic error and variability. While reading the materials, I realized that they are attempting to improve their work performance. I'm also going to work on enhancing our system's performance.

IV. Methodology & Experimentation

A. MRNET DATASETS

A total of 1,370 knee MRI tests were done at Stanford University Medical Centre for the MRNet dataset. The dataset comprises 1,104 abnormal examinations (80.6 percent), with 319 (23.3 percent) ACL tears and 508 (37.1 percent) meniscal tears; labels were extracted manually from clinical reports. In this study, the most prevalent justifications for knee MRI exams were acute and chronic pain, follow-up or preoperative assessment, and injury/trauma. Examinations were carried out using GE scanners (GE Discovery, GE Healthcare, Waukesha, WI) equipped with a standard knee MRI coil and a routine non-contrast knee MRI protocol that included the following sequences: coronal T1 weighted, coronal T2 with fat saturation, sagittal proton density (PD) weighted, sagittal T2 with fat saturation, and axial PD weighted with fat saturation. A 3.0-T magnetic field was employed in 775 (56.6 percent) of the tests, whereas the rest used a 1.5-T magnetic field[8].

MRNet is a CNN-based model trained on the MRNet dataset that translates a 3-dimensional MRI sequence to a probability in order to predict anomalies in knee MRI tests.

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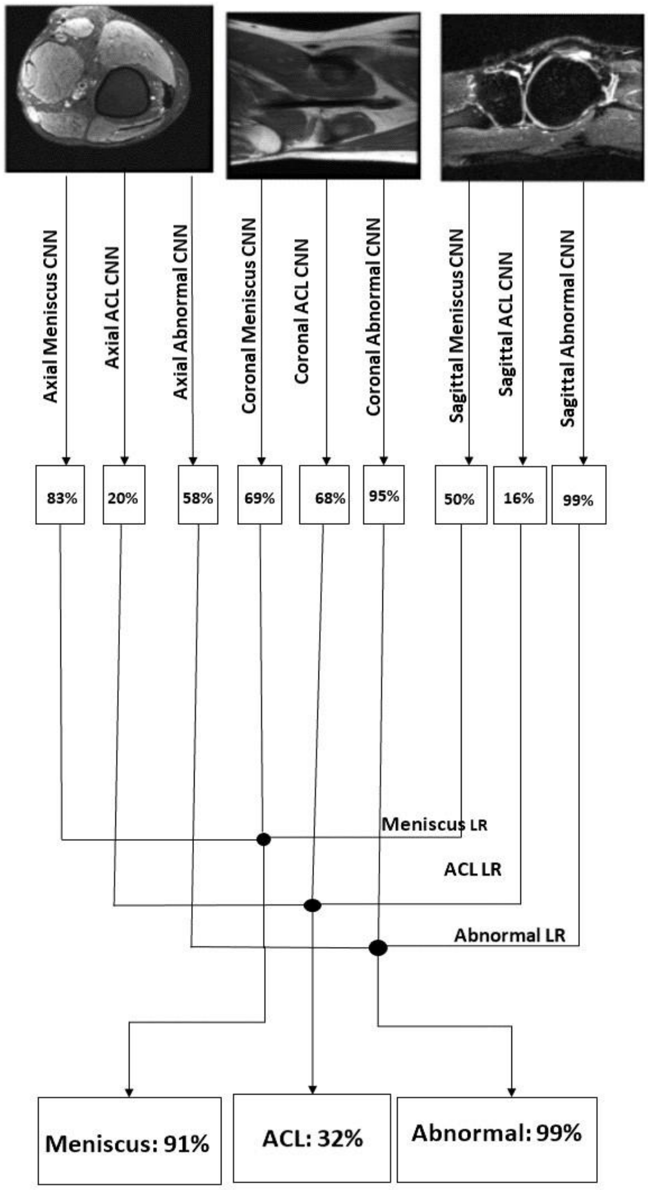

Fig.1 MRNet architecture [9]

B. *Computer Vision Using Deep Learning*

The scientific discipline of computer vision (CV) outlines how machines perceive the meaning of pictures and movies. Computer vision algorithms examine certain criteria in photos and videos and then apply interpretations to tasks that need prediction or decision-making. Deep learning algorithms are now the most widely utilised in computer vision. This article examines the many applications of deep learning in computer vision. You'll learn about the benefits of employing convolutional neural networks (CNNs), which have a multi-layered design that allows neural networks to focus on the most important aspects of a picture.

Convolutional neural networks (CNN) are used in modern computer vision techniques, and they give a significant performance boost over classic image processing algorithms. CNN's are multi-layered neural networks that are used to reduce input and calculations to the most relevant set over time. The data entered is then compared to known data in order to identify or categorize it. CNN's are commonly employed for computer vision applications, but they may also be utilized for text and audio analytics.

Deep learning methods have made it possible to create more accurate and complicated computer vision models. The usage of computer vision applications is becoming increasingly valuable as these technologies advance.

C. *VGG architecture*

VGG stands for Visual Geometry Group, and it is a multilayer deep Convolutional Neural Network (CNN) architecture. The term "deep" refers to the number of layers in VGG-16 or VGG-19, which have 16 or 19 convolutional layers respectively. The VGG architecture serves as the foundation for cutting-edge object recognition models. The VGG-Net, which was created as a deep neural network, outperforms baselines on a variety of tasks and datasets in addition to ImageNet. Let's understand the architecture with the help of example: -

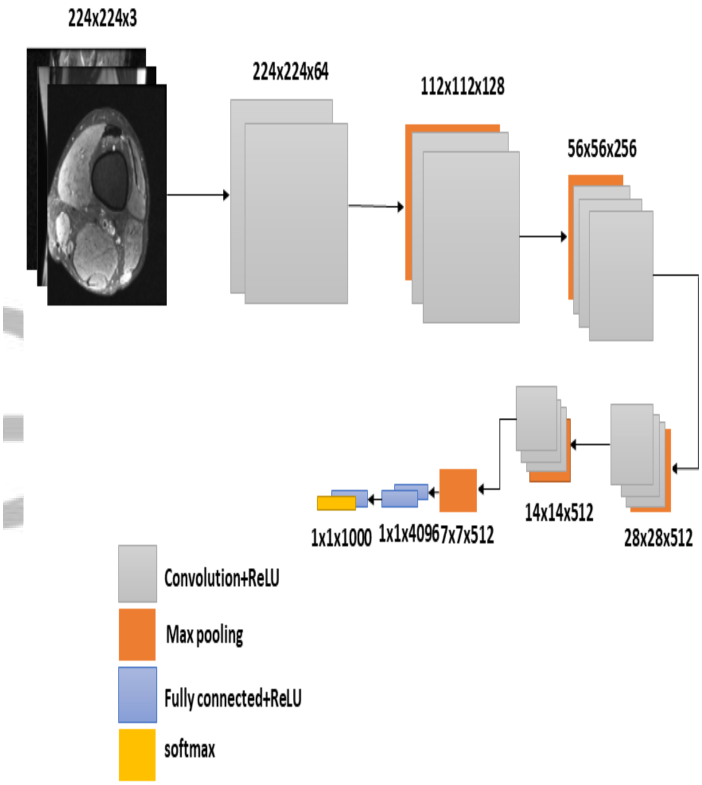

Fig.2 Example of VGG architecture

The VGG model, often known as VGGNet, is a convolutional neural network model introduced by A. Zisserman and K. Simonyan of the University of Oxford that supports 16 layers. In ImageNet, the VGG16 model achieves about 92.7 percent top-5 test accuracy. ImageNet is a collection with about 14 million photos divided into over 1000 categories. It was also one of the most popular models submitted to the 2014 ILSVRC. It makes considerable gains over AlexNet by replacing big kernel-sized filters with numerous 33 kernel-sized filters one after the other. The VGG16 model was trained over many weeks using Nvidia Titan Black GPUs. As previously stated, the VGGNet-16 has 16 layers and can categorize photos into 1000 different item categories, such as keyboards, animals, pencils, and mice. In addition, the model features a 224-by-224 picture input size. The VGG19 model (also known as VGGNet-19) has the same principle as the VGG16 model, with the exception that it supports 19 layers. The numbers 16 and 19 represent the number of weight layers in the model (convolutional layers). VGG19 thus has three additional convolutional layers than VGG16[10].

D. Process

We propose and analyze designs for training networks and outputting the probability of an ACL tear, meniscal tear, or other abnormalities on a patient's knee. The Resnet feature extractor and other layers put on top of the basic MRNet architecture were replaced with a more current design such as VGG-Net. For a number of classes, we changed the final layer to output a probability rather than a one-hot softmax vector. We utilized VGG-Net with pre-trained weights and transfer learning. Transfer learning functions as a good regulariser even when the pre-trained domain is considerably different, and the low-level characteristics learned on the original assignment appear to operate well in reality. We repeat the picture three times, once for each RGB channel, to guarantee the input dimensions are consistent with the pre-learned weights from Resnet, similar to how MRNet was trained. Furthermore, similar to MRNet, we input the slices in batches of one size and compute the maximum value of all the slices as the final probability before backpropagation tunes the weights. We utilize the SGD optimizer and cross-entropy loss, with loss scaled inversely proportionate to the number of samples in the dataset for that class. Because these networks are prone to overfitting, we also used data augmentation strategies and added a number of new image transformations, such as adjusting the contrast of an image by a random factor, applying random gamma adjustment, and randomly adjusting the brightness of the image, or randomly cropping the image.

The network training was made significantly quicker by not having to repeat the pictures three times, one for each channel, and by being able to train them in batches without having to compute the maximum of all probability forecasts, as discussed in this section. The data augmentation policy was the same as the previous technique, but without the three-channel transformations: Random Brightness, Contrast Limited Adaptive Histogram Equalization, and Random Brightness Contrast. We still calculated a probability for each patient and plane and used a Logistic Regression classifier to train each task, which included ACL injury, meniscal tear, and abnormalities. If we consider that the default slicing approach supplied is done vertically, we also cut the collection of photos or slices horizontally for each patient and for each task as an experiment. We used those inputs to train models, but the results were not as good as with vertical slicing. On the MRNet Dataset, we use image processing and a variety of transfer learning methods. When we used Vgg-Net on the MRNet dataset after that, we obtained incredible accuracy. We obtained model performance for an ACL tear, meniscal tear, and abnormalities in the axial plane, coronal plane, and sagittal plane. And the graph of performance is previously stated below: -

a) Examining the model's performance for abnormalities in the axial, coronal, and sagittal planes.

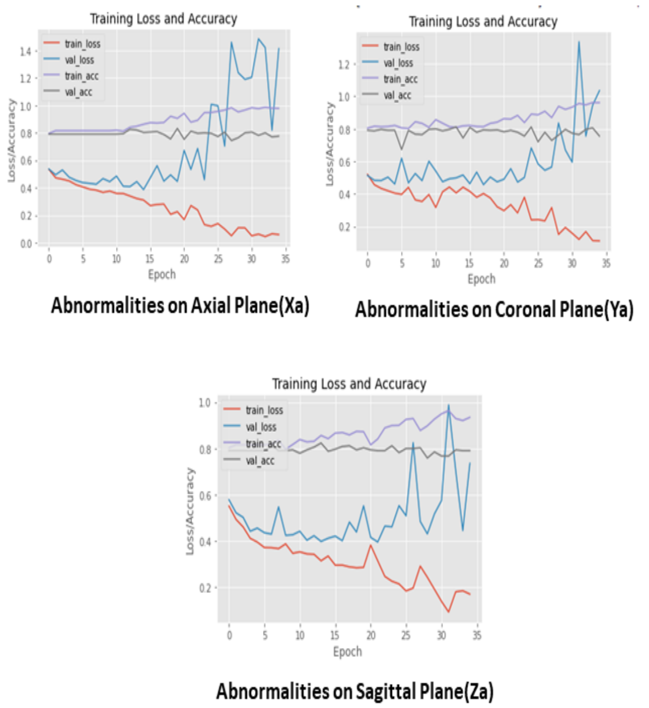

Fig.3 Abnormalities on axial, coronal, & sagittal planes

Calculating the Average accuracy:-

Abnormalities on Axial Plane (Xa)= 97%

Abnormalities on Coronal Plane (Ya)= 96%

Abnormalities on Sagittal Plane (Za)= 93%

Avg.= (Xa+Ya+Za)/3

= (97+96+93)/3

= 95.33%

On the axial, coronal, and Sagittal Planes, the average accuracy for Abnormalities is 95.33%.

b) Examining the model's performance for an ACL tear in the axial, coronal, and sagittal planes.

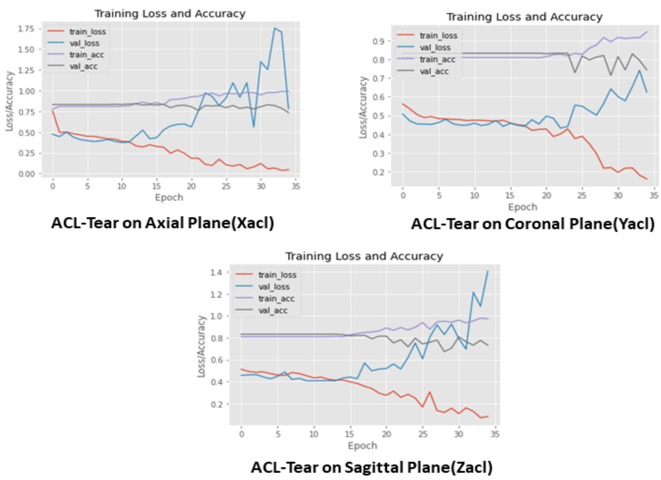

Fig.4 ACL-Tear on axial, coronal, & sagittal planes

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Calculating the Average accuracy:-

ACL tear on Axial Plane (Xacl)= 98%

ACL tear on Coronal Plane (Yacl)= 94%

ACL tear on Sagittal Plane (Zacl)= 97%

Avg.= (Xacl+Yacl+Zacl)/3

= (98+94+97)/3

= 96.33%

On the axial, coronal, and Sagittal Planes, the average accuracy for ACL tear is 96.33%.

c) Examining the model's performance for an meniscal tear in the axial, coronal, and sagittal planes.

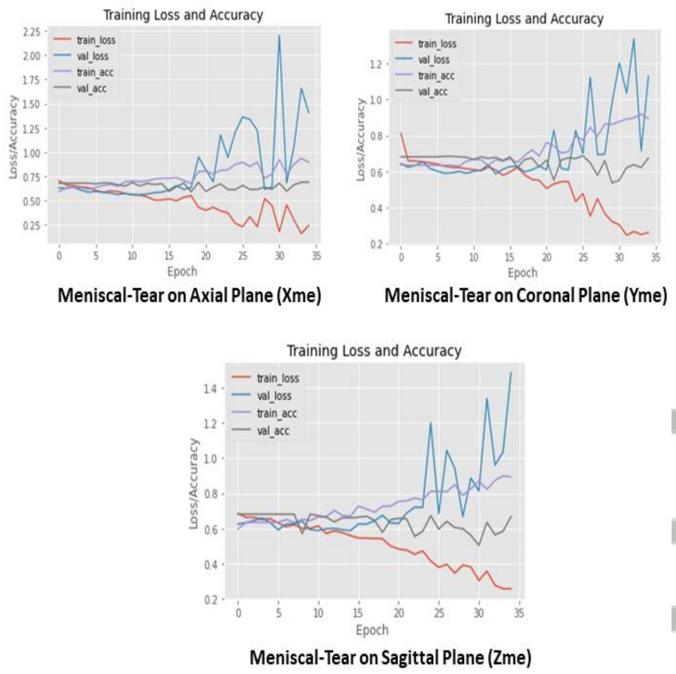

Fig.5 Meniscal-Tear on axial, coronal, & sagittal planes

Calculating the Average accuracy:-

Meniscal tear on Axial Plane (Xme)= 89%

Meniscal tear on Coronal Plane (Yme)= 89%

Meniscal tear on Sagittal Plane (Zme)= 89%

Avg.= (Xme+Yme+Zme)/3

= (89+89+89)/3

= 89%

On the axial, coronal, and Sagittal Planes, the average accuracy for Meniscal tear is 89%.

V. Results

We acquire improved accuracy for Abnormalities, ACL-tear, and Meniscal-tear of the knee on the axial, coronal, and sagittal planes after comparing the different transfer learning techniques we received when I utilized Vgg-Net on the MRNet dataset.

Model	Planes	Average Accuracy
ResNet	Axial Coronal Sagittal	93% 91% 85%
MobileNet	Axial Coronal Sagittal	94% 93% 87%
VGG-Net	Axial Coronal Sagitta	95% 96% 89%

Fig.6 Comparison Table

On the axial, coronal, and sagittal planes, the average accuracies are 95%, 96%, and 89%, and the average validation accuracies are 77%, 73%, and 67% for Abnormalities, ACL-tear, and Meniscal-tear, respectively. The bar chart below illustrates this:-

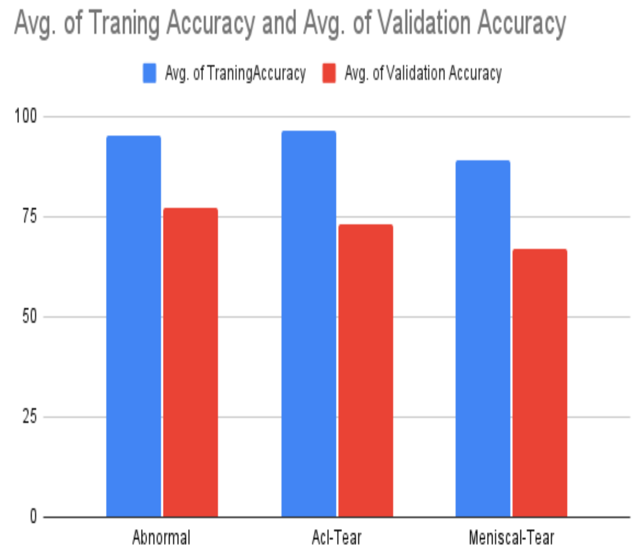

Fig.7 Bar Chart for showing results

VI. Conclusions & Future works

We discussed how to construct a deep learning architecture to increase classification performance on a dataset of MRI images of knees in this research. We developed, designed, and trained a set of deep learning models to predict the likelihood of an ACL tear, meniscus tear, or abnormal exam on a knee based on an MRI, and we used deep learning and CNN techniques on the MRNet dataset and benchmark. We had pictures from three planes for that: axial, coronal, and sagittal, as radiologists normally analyze an MRI from several perspectives and we reached the model's optimum performance.

As, in medical domain the accuracy of the results are of utmost importance. In the future, we would like to increase the accuracy of the classification by increasing the dataset variety and improving network architecture.

This research will also be converted to a product by deploying it in the cloud and networking with various hospitals, doctors and patients.

VII. References

[1] Antico M, Vukovic D, Camps SM, et al. Deep Learning for US Image Quality Assessment Based on Femoral Cartilage Boundary Detection in Autonomous Knee Arthroscopy. IEEE Trans Ultrason Ferroelectr Freq Control. 2020;67(12):2543-2552. doi:10.1109/TUFFC.2020.2965291

[2] MRI evaluation of knee cartilage - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/Classification-of-chondral-lesions-of-the-knee-Axial-MRI-A-to-C-and-sagittal-MRI-D_fig7_262700413 [accessed 26 Nov, 2021]

[3] Zhou, Zhaoye & Zhao, Gengyan & Kijowski, Richard & Liu, Fang. (2018). Deep Convolutional Neural Network for Segmentation of Knee Joint Anatomy. Magnetic Resonance in Medicine. 80. 10.1002/mrm.27229.

[4] A. Suponenkovs, Z. Markovics and A. Platkajis, "Knee-joint tissue recognition in magnetic resonance imaging," 2017 IEEE 30th Neumann Colloquium (NC), 2017, pp. 000041-000046, doi: 10.1109/NC.2017.8263280.

[5] A. D. Orsi et al., "Investigating the effects of knee joint motion schemes on knee joint injury: A finite element analysis," 2014 40th Annual Northeast Bioengineering Conference (NEBEC), 2014, pp. 1-2, doi: 10.1109/NEBEC.2014.6972895.

[6] Tsai, Chen-Han & Kiryati, Nahum & Konen, Eli & Mayer, Arnaldo & Eshed, Iris. (2020). Knee Injury Detection using MRI with Efficiently-Layered Network (ELNet).

[7] Bien, Nicholas, et al. "Deep-learning-assisted diagnosis for knee magnetic resonance imaging: development and retrospective validation of MRNet." PLoS medicine 15.11 (2018): e1002699.

[8] MRNet: A Dataset of KneeMRs and Competition for Automated Knee MR Interpretation [Online]. Available: https://stanfordmlgroup.github.io/competitions/mrnet/

[9] Stanford ML Releases MRNet Knee MRI Dataset [Online]. Available: https://medium.com/syncedreview/stanford-ml-releases-mrnet-knee-mri-dataset-9f44d7621131

[10] VGG Very Deep Convolutional Networks (VGGNet) - What you need to know [Online]. Available: https://viso.ai/deep-learning/vgg-very-deep-convolutional-networks/#:~:text=VGG%20stands%20for%20Visual%20Geometry,ground%2Dbreaking%20object%20recognition%20models.

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