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Original Article

Comparative Analysis of Deep Convolutional Neural Network for Detection of Knee Injuries

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Abstract - *Commonly occurring knee injuries such as Anterior Cruciate Ligament and Meniscus Torn lead to osteoarthritis problems in people. Radiologists very often recommend Magnetic Resonance Imaging for diagnosis of knee injuries. However, longer MRI interpretation time, vulnerability to clinical errors, and inconsistency are the major issues in the application of the MRI. The high volume of imaging and complexity of the patient's profile make the task time-consuming, thereby increasing the workload of radiologists. Deep Learning-based automated techniques can help radiologists identify high-risk patients and aid as a support system for decision-making. In this study, we focus on different types of pre-trained networks to perform the classification of Knee Magnetic Resonance Images. The proposed work comprises three different classifiers, viz. knee abnormality, meniscus tear, and ACL tear, for independently classifying these three labels. In the proposed framework, features from knee Magnetic Resonance Images (MRI) are extracted using three well-known backbone networks, namely NASNet Large, NASNet Mobile, and ResNet50, for classification purposes. We also propose a Deep Convolutional Neural Network (DCNN) with residual block and NASNet Large as a feature extractor. The performance of these networks is evaluated for the MRNet dataset published by the Stanford ML Group. Overall, we achieved a performance of 94.47% for knee abnormalities for NASNet Large on the sagittal plane, and ResNet50 achieved ACL accuracy of 91.78% on the sagittal plane. For meniscus tear detection, the proposed DCNN model outperformed the state-of-the-art with a performance of 85.82% on the axial plane. We found that the proposed framework and carefully fine-tuned the network architecture were crucial factors in determining the best performance.*

Keywords - *Knee injuries, Deep Convolutional Neural Network, MRNet dataset.*

1. Introduction

Deep Learning applications have extended over a diverse range of domains in the recent decade. Medical imaging analysis using Deep Learning has become a research hotspot [18]. Medical data, especially imaging data, has grown substantially in the last few years due to the existing practice of Evidence-Based Medicine (EBM). EBM uses the best available scientific observations in making decisions for patient care. EBM is a means to make available methodical medical datasets consisting of clinical records and data in various forms, along with image data such as CT scans, MRI images, X-rays, whole slide images, etc. Radiologists are now more attuned to working in diagnosing such medical imaging data.

The complexity of anatomical structures makes the interpretation of medical images a formidable task. A Radiologist needs to communicate the findings and impressions in the patient's report in a short period of time. Deep Learning plays a critical role in disease detection related to joints in clinical radiology and performs accurate imaging analysis to provide a faster and more promising solution. However, these techniques are not restricted to patient diagnostics; they have broadened their scope to include drug discovery, insurance fraud, genome analysis, etc. One of the main advantages of Deep Learning is that the manual specification of features is not required, as the machine can learn on its own through training on a dataset [1].

However, Deep Learning is not commonly used for knee imaging diagnosis because of the complex anatomical structure of the knee joints [23]. MRI is the most effectively used diagnostic tool for evaluating and examining knee pain, as it provides a comprehensive assessment of soft tissues and bone structures. It is the most accurate and effective technique to detect knee joint defects. Particularly as applied to the knee joint, the MRI accurately assesses soft tissues, bone fragments, and surrounding tissues.

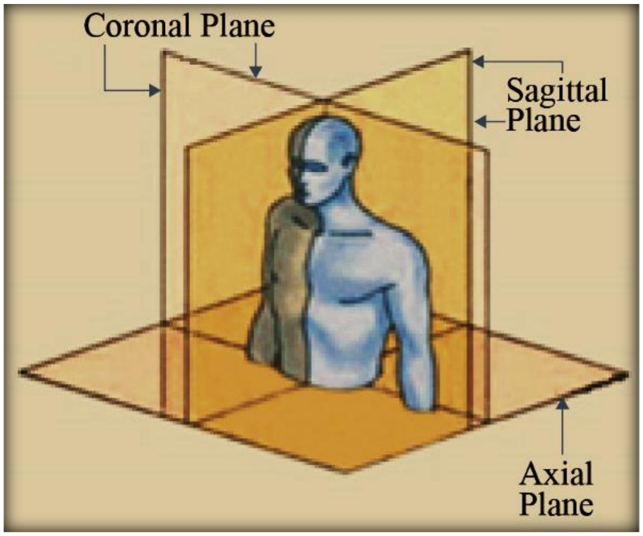


Fig. 1 Coronal, Sagittal and Axial MRI planes [2]

As depicted in Figure 1, the MRI scan is taken in three distinct orientations, viz. sagittal, coronal plane, and axial plane [2]. The sagittal plane can be viewed from the side, the axial plane can be viewed from the bottom, and the coronal plane can be viewed from the front.

Proper interpretation of knee MRI involves scanning all the images of all three orientations and summarizing the findings in the form of an impression in the report [3]. Radiologists typically read these images to identify and locate any abnormalities or lesions present. Analyzing various other attributes of lesions helps them provide detailed and in-depth reports related to these lesions. This standard routine procedure is time-consuming and may have certain significant anomalous results [4]. However, with the recent growth in technology, Deep Learning automated knee image analysis has made diagnosis simpler and faster. It can help medical practitioners or radiologists provide quick prognoses and detect high-risk patients [1-3]. This paper aims to put forward the technique pertaining to Deep Transfer Learning to help predict various knee abnormalities. For this study, we shall utilize a public dataset of knee MRI images, viz., the MRNet dataset [5]. The research of the related work of [6],[7] has motivated this study and contributed to our designing a novel deep Convolutional Neural Network (CNN) with pre-trained models such as NASNet Large, NASNet Mobile, and ResNet50. The following points provide the specific contributions of the paper:

- In order to develop a novel architecture for the classification of knee abnormality using MRI images, Transfer Learning (TL) approaches were introduced and implemented, such as NASNet Large, NASNet Mobile, and ResNet, as feature extractors at the preliminary stage.
- We propose a Deep Convolutional Neural Network (DCNN) with residual block, which outperformed the state-of-the-art with the performance of 85.82% on the axial plane.
- A comparative analysis is conducted for a set of classification models for knee abnormality using the MRNet database. The architecture consists of 3 different classifiers for independently classifying knee abnormality, meniscus tear, and Anterior Cruciate Ligament (ACL) tear.

The research paper puts forth the related work in sections as follows: Section 2 evaluates the previous related study in the field pertaining to Deep Learning and its extensive utilization in medical image processing. We introduce the dataset and the general structure of the proposed architecture in Section 3 and Section 4, respectively. Section 3 also includes a detailed explanation of the MRNet dataset. Further, Section 5 presents the experiments performed using various pre-trained models and provides the observations and interpretation of results. Finally, Section 6 is the conclusion of our work.

2. Literature Review of Related Work

An abundance of significantly improved results achieved by Deep Learning models has led to an enormous amount of research work to be published in medical imaging using Machine Learning and Deep Learning approaches [4-8]. Numerous research studies focus on Deep Learning applied to image analysis related to medical issues and particularly concentrate on chest-related diseases, brain abnormalities and tumors [9], lung disorders [2], etc. The following literature review discusses several deep network approaches used in the past by researchers for knee image analysis and is also an invaluable component of this research project.

In the study on knee MRI by Kamel Rahouma et al. [4], pre-trained models such as NASNet Mobile Network were used to classify the MRNet images for knee disease. In this work, the CNN model was built for feature extraction through MR images, and Machine Learning approaches were used to classify those images as compared to other approaches. The Random Forest classifier was found to have given better accuracy. As per the study, knee abnormalities were detected with an accuracy of 91%, meniscus tear with 85%, and ACL with an accuracy of 88%. The work presented in the paper [14] achieved better results on the MRNet dataset, but it had limitations in terms of image slice selection. A slice selection approach was used [6] to design the sequential CNN along with ResNet50, but this requires high computational power.
Bien et al. [5] investigated Deep Convolutional Neural Networks (DCNNs) for feature extraction and utilized them for detecting ACL tears, meniscus tears, and knee abnormalities. The authors used a CNN model and utilized it to extrapolate the image representation. The study achieved an area under the receiver operating characteristic curve (AUC) values of 0.937, 0.965, and 0.847, respectively, on the internal validation set. Using Deep Learning, Kara et al. [6] have worked on an MRI dataset associated with knee joints. This study employs a deep neural network with the Stanford

Machine Learning Group MRNet images to check for an ACL tear. It also helps to detect the meniscus tear or the presence of knee abnormalities. The work comprises mainly three sections: 1. Selection of appropriate images, 2. Selections of eligible images are identified by considering several aspects of images like the disturbance under examination, noisiness, and damaged images.

Naveen Subhas et al. [15] study employs a Convolution Neural Network (CNN) model integrated with the ResNet50 model. The authors put forth their findings stating an accuracy of 0.83 in the finding an ACL tear in the axial plane, 0.89 in the detection of the presence of abnormality in the axial plane, and an accuracy of 0.77 in the diagnosis of a meniscus tear in the sagittal plane.

Azcona et al. [7] discussed several existing Deep Learning models and implemented the residual network to evaluate the probability of knee injuries. The authors utilized the ResNet18 model to calculate the probability of knee abnormalities, the probability of an ACL, and the meniscus tear. A fixed number of slices of all the data and logistic regression as a classifier were used to train the model for each task with 0.934 AUC on validation data. Here, a fixed number of slices were considered in the mathematical operations. This procedure intends that the middle slice may have significant data comparable to the rest of the MRI sequence. Tsai et al. [8], instead of a transfer learning approach, put forward an effective architecture to diagnose knee abnormalities. It was labeled as the Efficiently Layered Network (ELNet) architecture. The highlight of this approach was to combine the multi-slice normalization along with a downsampling of the Blur Pool technique in the network.

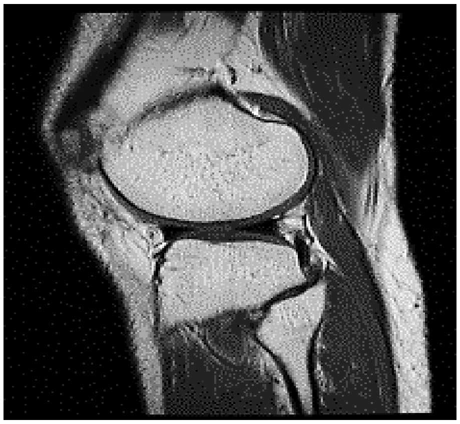
In the study of Fang Liu et al [17], axial plane images were employed to detect ACL tear and knee abnormalities rather than coronal or sagittal, whereas coronal plane images were used to pinpoint meniscal tears. The evaluation statistics were better for various performance metrics as compared to MRNet architecture. The ROC-AUC values of 90.4%, 96%, and 94.1% for meniscus, ACL, and abnormality diagnosis, respectively, were achieved. We have identified the limitations of previous studies utilizing a CNN-based approach for knee abnormality classification. Table 1 shows the pros and cons of existing classification studies on the MRNet dataset and presents our proposed research.

3. The Knee MRI Dataset

Section 3 briefly presents the dataset availability and data preparation required for a Deep Learning approach employed in our work.The datasets used in this study consist of the MRNet dataset published by Stanford University Medical Center (SUMC) [10], available on the internet for reference. This dataset consists of knee MRI images acquired with three planes, viz. sagittal plane, axial plane, and coronal plane [11]. Each sample in the dataset has a varied number of slices with these three planes. Fig. 2 shows a sample MRI image with these three planes [12].

Table 1. A Literature Review of Classification Studies on MRNet Dataset

Author	Method	Pros	Accuracy
Nicholas Bien et al. (2018) [5]	MRNet DCNN	• It is more generalizable for the classification of knee abnormalities • The model is validated on a retrospective dataset, which gives more confidence in the results.	Meniscus Tear 0.735 ACL Tear 0.9 Abnormality 0.883
Chen-Han Tsai et al. (2020) [8]	Efficient Net	• Proposes ELNet for knee injury detection.	Meniscus Tear 0.88 ACL Tear 0.904 Abnormality 0.917
D Azcona et al. (2020) [7]	ResNet18	• Comprehensive comparison of existing and proposed new Deep Learning methods for detecting knee injuries.	Meniscus Tear 0.78 ACL Tear 0.84 Abnormality 0.85
Ali Can Kara et al. (2021) [6]	ResNet50	• Achieved high accuracy in detecting ACL tears. • The method can also identify the location and orientation of tears, which is important for diagnosis and treatment.	Accuracy obtained for Sagittal Meniscus Tear 0.7712 ACL Tear 0.7881 Abnormality 0.8898
Kamel Rahouma et al. 2021 [4]	NASNet Mobile	• Use NASNet Mobile Network, which makes it faster and easier to train a Deep Learning model for knee injury classification.	Maximum accuracy: Meniscus Tear 85% ACL Tear 88% Abnormality 91%
Kavita Joshi et al. 2022 [16]	Compact Parallel CNN	• The proposed model is a compact model for ACL tear detection	Overall accuracy of 96.60%

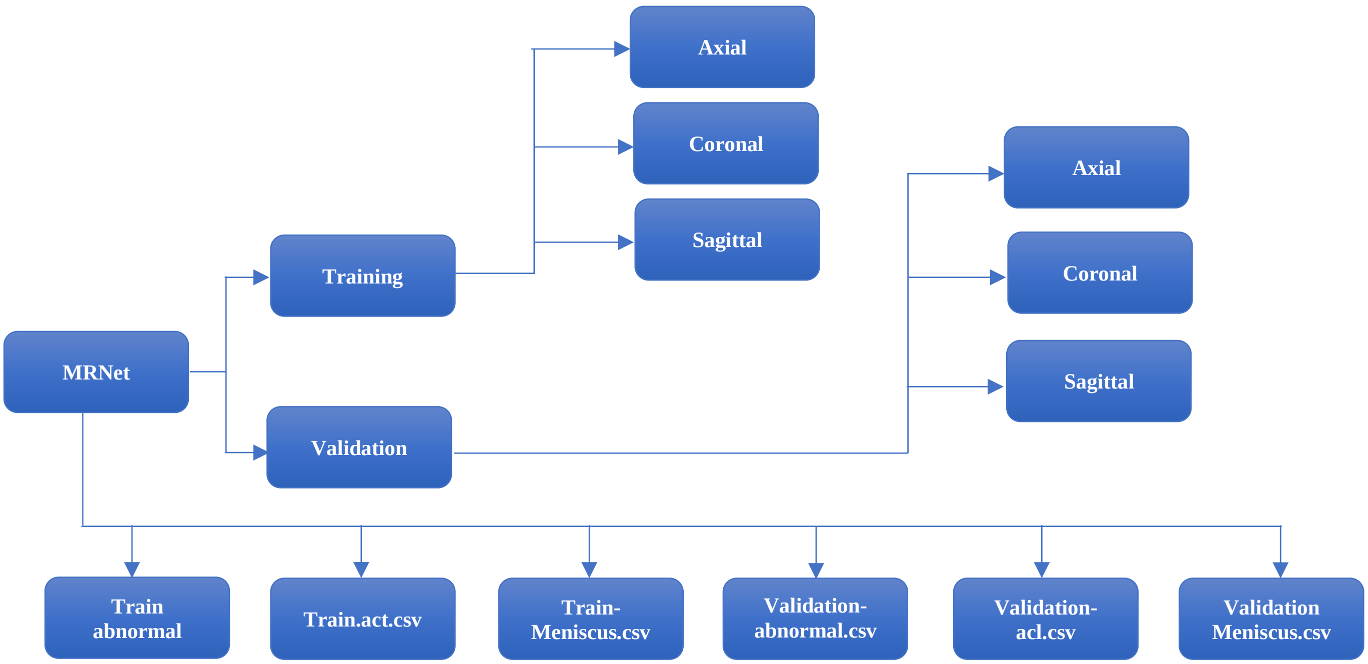


a) Sagittal MRI slice

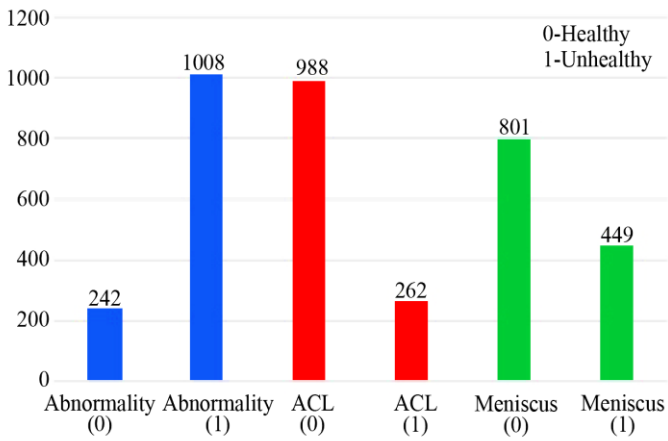
b) Coronal MRI slice

c) Axial MRI slice

Fig. 2 Sample MRI Images in three different planes: (a) Sagittal, (b) Coronal, c) Axial



(a)



(b)

Fig. 3. a) Structure of MRNet dataset b) Data Distribution

Fig. 3a visually presents the structure of the MRNet dataset, providing a comprehensive overview of its organization. The dataset exclusively comprises knee MR images in. npy format for efficient data handling and processing. The .npy file is available in (s, 256, 256), where ‘s’ represents the number of slices of each sample. The labels of each sample in the database are based on knee abnormalities, ACL tear, and meniscus tear. The labels for samples are provided in six different csv files, such as abnormal.csv, acl.csv, and meniscus.csv, for training data and the validation set.

This MRNet dataset consists of 1,370 knee MRI imaging records, and it was split into predefined sets of training data of 1130 sample sizes and validation data of 120 samples. The dataset holds 1,130 abnormalities records, which include 319 ACL tears and 508 meniscal tears. The data distribution of the MRNet dataset is depicted in Fig. 3b, and the number of patients in each class differs significantly, which shows a class imbalance problem in the dataset. The dataset comprises noisy images, and it was a challenging task to exclude these images due to the varied range of slices with respect to each plane. These noisy and damaged imaging records could lead to misclassification.

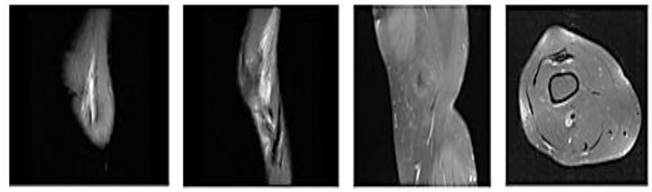


Fig. 4 Sample Examples of non-eligible images

In this work, removing such non-eligible records was carried out as a preliminary task based on a random sampling approach and a referring list mentioned in [6]. Figure 4 illustrates some non-eligible sample images.

4. Proposed Methodology

In this section, the block diagram of the proposed methodology is shown in Figure 5. The classification is performed separately on a single imaging stack (sagittal, axial, or coronal) as input image. The proposed approach consists of pre-processing the image data, feature extraction of input images using a transfer learning model, and classifying labels separately using 2D CNN [13]. We propose a convolutional neural network for classifying knee abnormalities based on labels provided by the MRNet dataset.

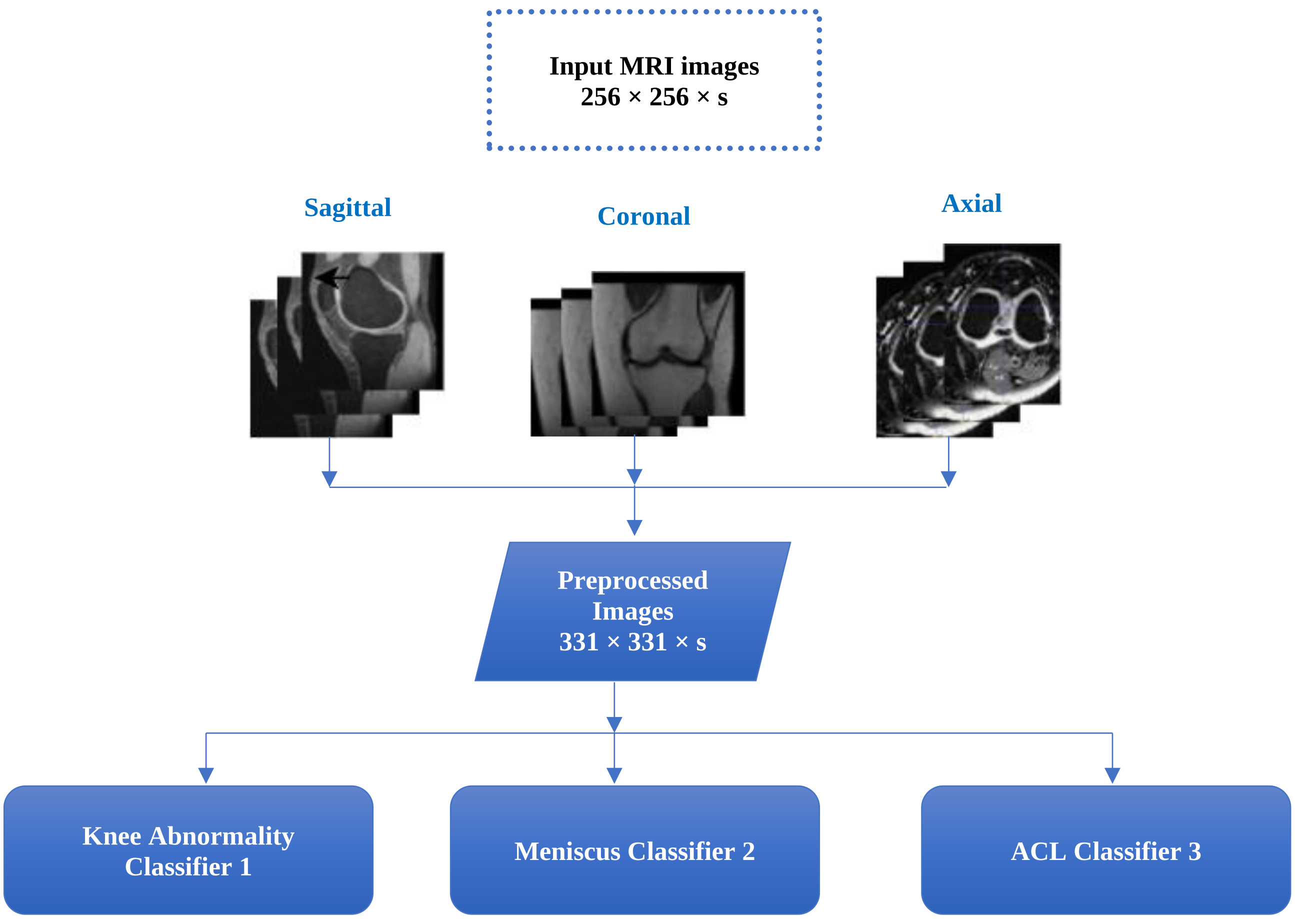


Fig. 5 Block diagram of convolutional neural network for Knee MRI classification

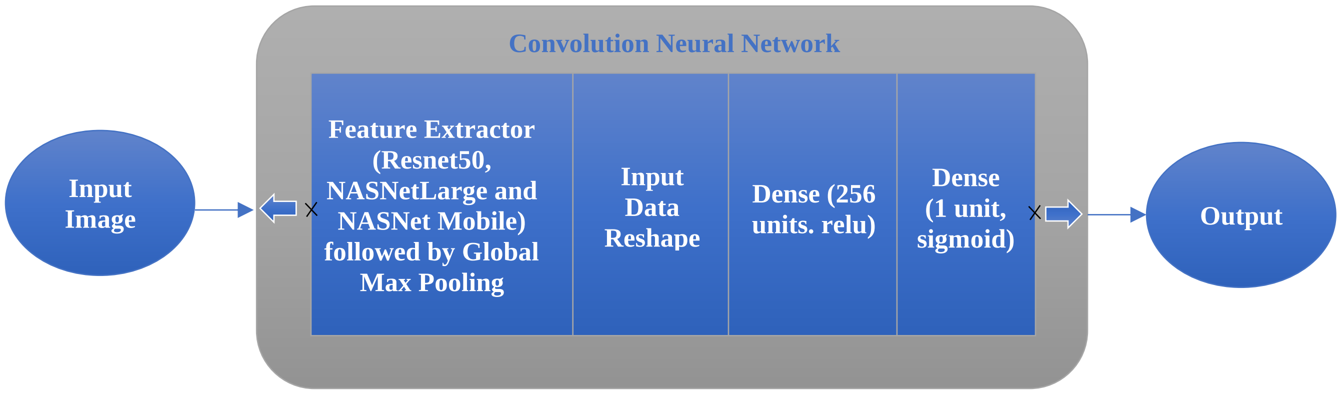


Fig. 6 Illustration of the CNN architecture using the pretrained model as feature extractor

This study creates three different classifiers based on the same training sets; each classifier network comprises different labels. Classifier 1 is trained to detect knee abnormality, Classifier 2 for healthy meniscus or torn meniscus, and Classifier 3 for detecting ACL tear. Firstly, various pre-trained models suitable for knee MRI imaging based on the ImageNet dataset were studied. Various parameters, such as accuracy, speed, and size, were considered while selecting the appropriate pre-trained model [4]. Finally, based on these parameters, pre-trained models such as NASNet Large, NASNet Mobile, and ResNet50 were used as feature extractors for detecting knee abnormalities, meniscus tears, and ACL tears. These models were pre-trained through ImageNet [13] and are suitable to work with three-channel images. We build our CNN model based on these pre-trained models, and the illustration of our model is depicted in Fig.6. The original knee image of the MRNet dataset has 256 × 256 × 1 as input size.

The repeat function generates the image size 256 × 256 × 3 for the three-channel images, which is the size for the input image to this pre-trained model. Feature extraction through the pre-trained model is followed by global max pooling to reduce the dimensionality. These extracted features were stored in the external file separately for all three planes, viz., the sagittal, coronal, and axial planes of each sample.

These features were used as input feature maps for the succeeding layer of CNN architecture. These input features get a tensor of shape s, 2048, and reshaped into 2048, s, where s is the number of slices in the MRI sequence.Further, this sequential CNN network involved two consecutive dense layers using the sigmoid activation function in the last dense layer to obtain output as 0 or 1, as 0 or 1 indicates the prediction of the sample as healthy or unhealthy. We then compiled our model using Stochastic gradient descent (SGD) as the optimizer and binary cross entropy as loss. SGD learning with momentum for sagittal, axial, and coronal features was employed to train the model. With due consideration, the learning rate was initially set to 0.001. To get good results, the momentum was set to 0.9.

In the second implementation, we propose a deep convolutional neural network (DCNN) that implements a neural network model with a residual block [19].

Residual learning is a technique that allows neural networks to learn residual functions instead of mapping the input directly to the output. This approach may lead to improvements in accuracy or speed of inference at run time and enables the network to focus on learning the difference between the input and output, which can be easier for the network to learn. We utilized NASNet Large architecture as a feature extractor and extended this architecture by integrating residual blocks in the network, as depicted in Figure 7.

The idea is to introduce a shortcut or skip connection that facilitates the smooth flow of information from one layer to the layer two steps ahead. This skip connection allows the network to bypass the normal Convolutional Neural Network (CNN) flow and propagate data directly from one layer to the layer after the immediate next.The basic structure of the Residual network is shown in Figure 8. Instead of directly learning the desired function H(x), the network is trained to fit the residual mapping [19] using (1).

$$H(x) = F(x) + x \tag{1}$$

Where H(x) represents the desired mapping, F(x) represents the residual mapping to be learned, and x is the input. By adding the residual mapping F(x) to the input x, the network can effectively learn the difference between the desired output and the input rather than attempting to learn the entire mapping from scratch.

The proposed architecture begins with an input layer that takes in data with 2048 features. Following the input layer is a fully connected layer with 331 units, utilizing the rectified linear unit (ReLU) activation function. This layer aims to transform the input data into a higher-dimensional representation, facilitating the extraction of complex patterns.

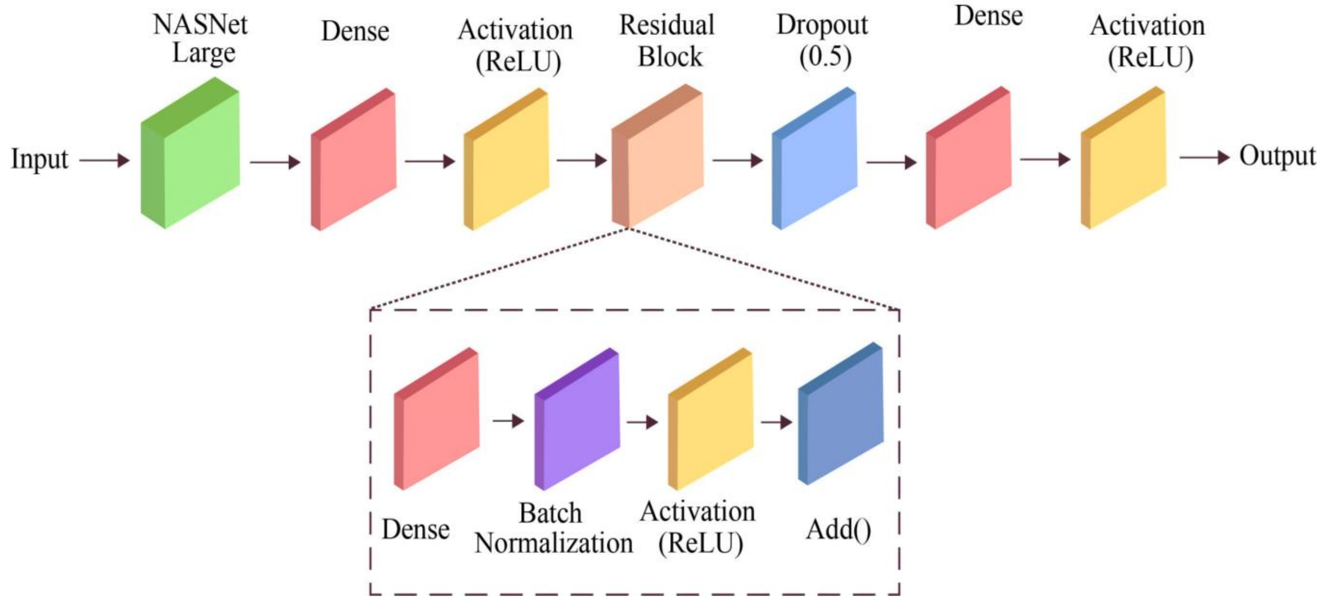


Fig. 7 Deep convolutional neural network architecture based on NASNetLarge with residual block

A residual block is introduced to incorporate the concept of residual learning. This block starts with a fully connected layer, similar to the previous layer, which processes the input data. The resulting transformed data is then normalized using batch normalization, which enhances the stability and efficiency of the network. The output of the residual block is obtained by adding the transformed data to the previous model output, allowing the network to focus on learning the residual mapping.

A dropout layer with a rate of 0.5 is applied to mitigate overfitting. This layer randomly sets 50% of the units to 0 during training, preventing the network from relying too heavily on specific units and promoting more robust representations. Finally, the output layer, consisting of a single unit with sigmoid activation, is added. This layer provides the binary classification prediction, producing a probability-like output indicating the likelihood of the input belonging to a particular class.

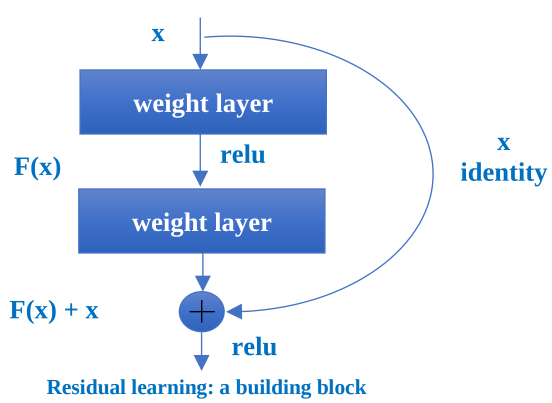


Fig. 8 Residual learning [19]

4.1. Training Model

The MRNet dataset consists of a number of MRI cases, where each case is represented by axial, coronal, and sagittal. Every dataset image is 256 × 256 × s, where s is the number of slices for each case and falls in the range of 17 to 61 slices. The analysis was carried out to select the slices regarding the model performance appropriately.

The proposed methodology was to train with two different settings depending on the number of slices chosen for each MRI:
1. Consider all the slices of each sample/case.
2. Considers middle 9 slices. To get the middle 9 slices of each MRI sample, the function is written to get the middle slice, subtract and add 4 to get four equal numbers of slices on both sides of the middle slice. This allows us to include only the middle 9 slices of each MRI sample. Figure 8 depicts the sample images of the MRNet database with a middle 9 selection of images.

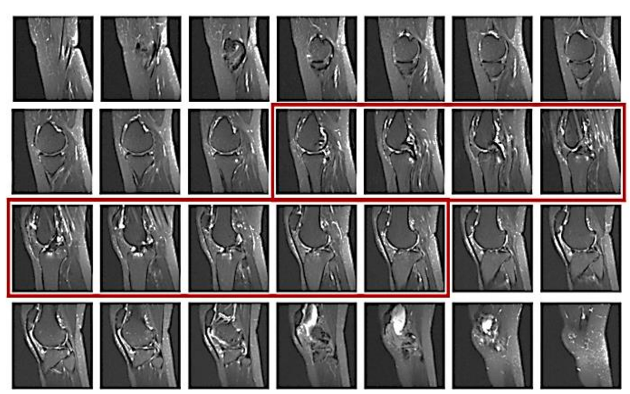


Fig. 9 Sample images of MRNet database with middle 9 selection of images

Using these two approaches, various model training is performed for MRNet database combinations. We trained a total of 54 models, 9 using NASNet Mobile, 9 using NASNet Large, and 9 using ResNet50, 9 using NASNet Large (Middle 9 slices), 9 using ResNet50 (Middle 9 slices), 9 for DCNN using NASNet Large with Residual Learning.

5. Experiments and Results

The proposed system was implemented using the Keras library in Python programming. We utilized a core i5 processor, 8 GB RAM, and Windows OS.

5.1. Evaluation Metrics

In the proposed scheme, we used the accuracy metric to measure the classification performance using Equation (2) as given below:

$$Accuracy = \frac{\sum TP + \sum TN}{\sum TP + \sum FP + \sum TN + \sum FN} \quad (2)$$

Where TP represents true positives, FP means False Positives, TN means True Negatives, and FN is the False Negatives.

5.2. Classification Results

Our study aimed to evaluate the proposed network's performance and compare it with the pre-trained models to detect knee abnormalities by utilizing the available source through Standford's MRNet Dataset.

The detailed experimental results of each classifier were provided from Table 2 to Table 5. We trained ResNet50 and NASNet Large using two different settings as middle 9 slices and all slices. We observed that the average accuracy achieved using the middle 9 slices and all slices is similar, especially for the classification of ACL and meniscus tears. There was not much improvement in the results considering the number of slices compared to the middle 9 slices, except for the classification of knee abnormalities.

Table 2. Comparison of all models trained for Abnormal MRI exam

Pre-trained Model/ Plane	Average Validation Accuracy (%)		
	Sagittal	Axial	Coronal
NASNet Mobile	85.43	88.55	88.26
NASNet Large	94.47	89.73	91.98
NASNet Large (Middle 9 slices)	90.91	90.12	91.23
ResNet50	90.57	87.14	85.80
ResNet50 (Middle 9 slices)	86.51	81.97	89.54
DCNN with Residual Learning (Proposed Approach)	84.13	84.93	87.38

Table 3. Comparison of all models trained for ACL Tear of MRI exam

Pre-trained Model/ Plane	Average Validation Accuracy (%)		
	Sagittal	Axial	Coronal
NASNet Mobile	88.28	84.53	85.17
NASNet Large	89.04	86.88	88.29
NASNet Large (Middle 9 slices)	88.29	88.78	88.29
ResNet50	91.78	88.84	83.46
ResNet50 (Middle 9 slices)	91.12	88.49	88.49
DCNN with Residual Learning (Proposed Approach)	88.01	88.62	82.80

Table 4. Comparison of all models trained for Meniscus Tear of MRI exam

Pre-trained Model/ Plane	Average Validation Accuracy (%)		
	Sagittal	Axial	Coronal
NASNet Mobile	60.84	67.84	49.07
NASNet Large	60.15	63.21	60.39
NASNet Large (Middle 9 slices)	65.31	58.17	59.01
ResNet50	70.85	74.07	73.06
ResNet50 (Middle 9 slices)	63.31	84.30	62.13
DCNN with Residual Learning (Proposed Approach)	82.05	85.82	83.82

Table 5. NASNetLarge with and without dropout layer

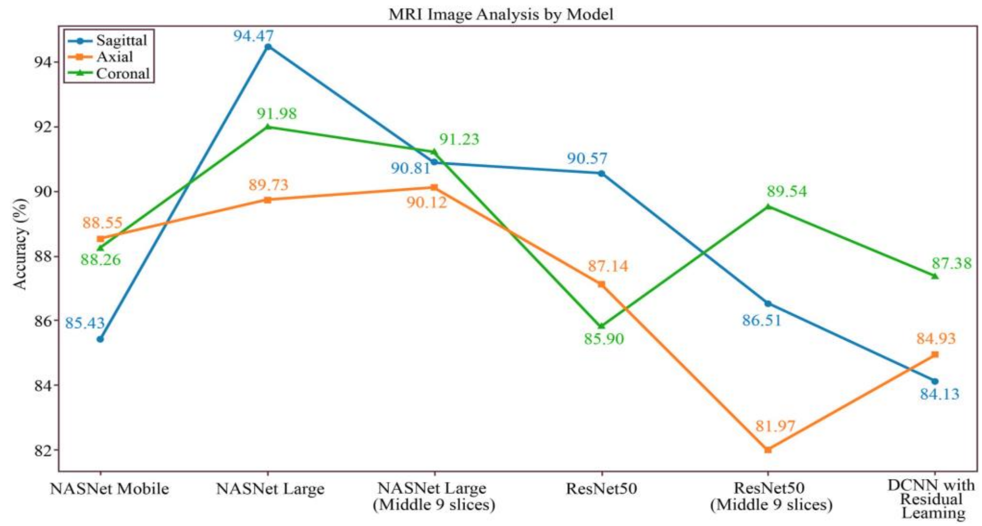
Abnormal accuracy (%)			
Pretrained Model/ Plane	Sagittal	Axial	Coronal
NASNetLarge	94.47	89.73	91.98
NASNetLarge dropout=0.5	96.39	86.33	92.00
ACL Accuracy (%)			
NASNetLarge	89.04	86.88	88.29
NASNetLarge dropout=0.5	89.04	86.88	88.29
Meniscus Accuracy (%)			
NASNetLarge	60.15	63.21	60.39
NASNetLarge dropout=0.5	61.15	61.82	62.25

5.2.1. Comparison of Abnormal MRI

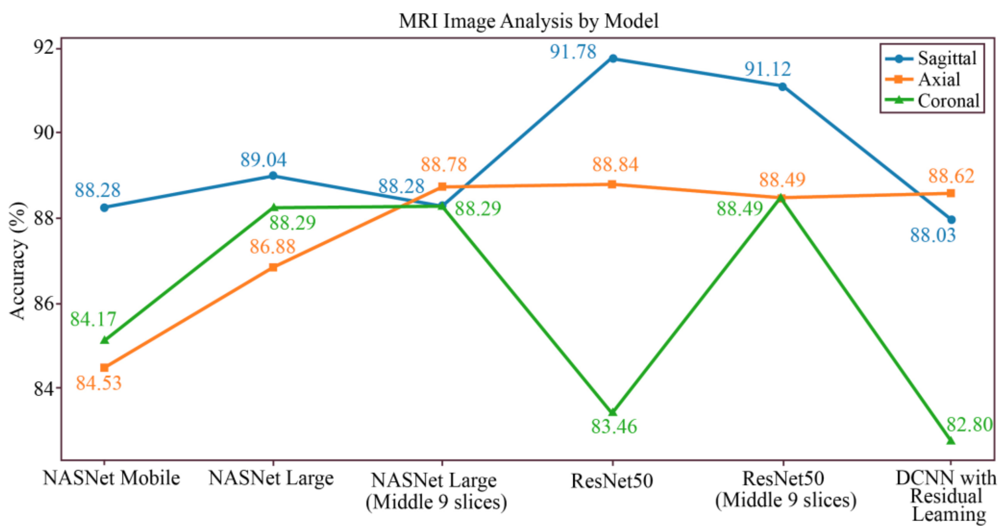
In the case of abnormal MRI, NASNet Large models were trained well and achieved the best results in the sagittal plane with 94.47% average validation accuracy. The accuracy score using all the slices is slightly better than the pre-trained model using the middle 9 slices. Table 2 shows the comparison of all models trained for Abnormal MRI exams.

5.2.2. Comparison of ACL Tears

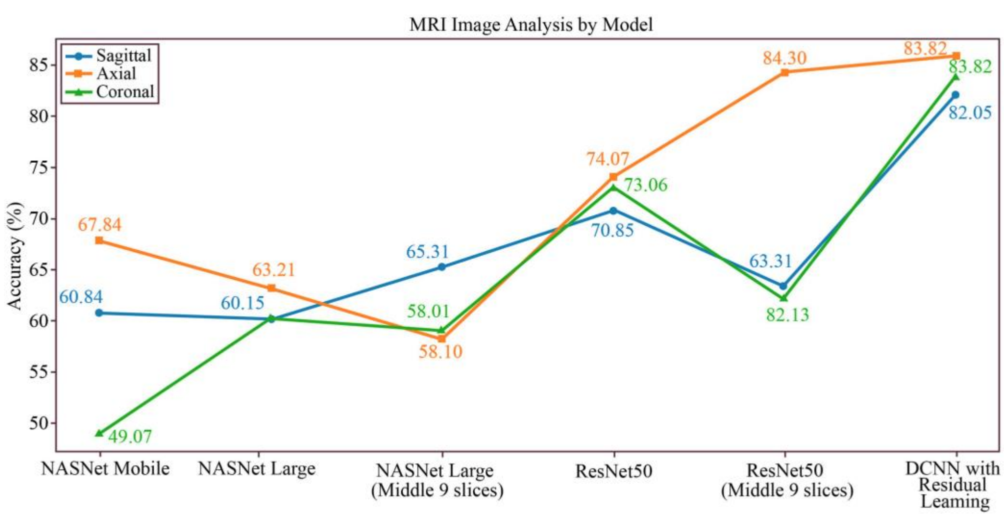
In the case of ACL tears, where the models were trained using a sagittal plane, *ResNet50* achieved the best average accuracy score of 91.78%. Here, the accuracy achieved using all slices and the middle 9 slices were quite close. It is always feasible to train models using the middle 9 slices rather than taking all the slices to reduce the computational power required to classify ACL tears.



(a) General abnormality classification



(b) ACL tear classification



(c) Meniscus tear classification

Fig. 10 Accuracy stats for each model and each diagnosis type: (a) general abnormality classification, (b) ACL tear classification, (c) meniscus tear classification

Table 6. All three Classifiers using DCNN with Residual Block

DCNN with Residual Learning (Proposed Approach)	**Highest Validation Accuracy (%)**		
	Sagittal	Axial	Coronal
Abnormal MRI	88.24	82.35	91.18
ACL tears	88.65	88.71	85.88
Meniscus tears	**85.24**	**98.18**	**85.29**

Table 7. Comparison with other classification approaches based on the MRNet database

Author (Year)	**Method**	**Accuracy %**
Nicholas Bien et al. (2018) [5]	DCNN	95.00%
Chen-Han Tsai et al. (2020) [8]	Efficient Net	91.05%
D Azcona et al. (2020) [7]	ResNet18	93.40%
Ali Can Kara et al. (2021) [6]	ResNet50	81.27% (Sagittal view)
Kamel Rahouma et al. 2021 [4]	NASNet Mobile	Abnormalities 91%, Meniscus tear 85% and ACL accuracy 88%
Proposed Framework		Abnormalities 94% (Sagittal), Meniscus tear 85.82%(Axial) ACL 91% (Sagittal)

5.2.3. Comparison of Meniscus Tears

In the proposed methodology, in the case of meniscus tears, it was found that the models trained on axial plane MRI using ResNet50 middle 9 slices delivered the best outcome. Here, the accuracy was achieved using the middle 9 slices, and all slices were quite close for NASNetLarge compared to ResNet50. To get the best accuracy, the DCNN with Residual Learning model was trained using all slices and achieved excellent results on all the planes for classifying a meniscus tear.

DCNN with the Residual Learning model outperformed the state-of-the-art with a performance range of 82.05 to 85.82% on all planes. Similarly, we also experimented using the NASNetLarge model by using a dropout rate of 0.5 for the added dropout layer for the classification of knee abnormal disease, meniscus, and ACL. It is observed and put forth in the comparison table which shows that the accuracy with dropout is better as compared to without dropout with a minor difference of 1 to 2%. The proposed DCNN approach provides the performance of All three Classifiers presented in Table 6 and achieved excellent performance compared to state-of-the-art networks based on the MRNet database for meniscus tear classification on all the planes.

5.3. Comparative Analysis

The performance of the proposed DCNN is also compared with other state-of-the-art networks based on the MRNet database, as shown in Table 7. From this table, it can be observed that our approach could achieve better results than the existing approaches.

6. Discussion

As seen from the earlier section of the model evaluations, this investigation presents the most extensive evaluation of CNN models on the MRNet database. The performance of the proposed system was compared with previous deep-learning-based classification techniques, as shown in Table 7.

This study examined various pre-trained models and implemented three pre-trained models, such as NASNet Large, NASNet Mobile, and ResNet50, suitable for Knee MRI images. We built three classifiers, namely knee abnormalities, meniscus tear, and ACL tear. Figure 10 displays the graph for each classifier and presents the accuracy score for each model. The proposed DCNN system has significantly improved meniscus tear detection classification compared with previous deep-learning-based approaches for meniscus tear detection.

7. Conclusion

A considerable amount of good work has already been published on Knee MRNet data analysis using Deep Learning. However, at the preliminary stage, we implemented, trained, and evaluated the pretrained model as NASNet Large, NASNet Mobile, and ResNet.

For that, we also studied the knee MRI image with three different orientations: sagittal, axial, and coronal. We proposed a DCNN based on NASNet Large with residual learning to classify knee abnormality using the MRNet database. Moreover, we deployed residual learning blocks in the network for critical feature extraction, improving the performance.

The proposed system yielded a maximum accuracy of 94.47% for Knee abnormalities classification on the sagittal plane by NASNet Large, 85.82% for meniscus tear on the axial plane by DCNN with residual network, and 91.78% for ACL tear detection on the sagittal plane. Our best-performing models, NASNet Large and ResNet50, were trained using the middle 9 slices and all slices for each MRI sample.

It is observed that the model performance is better using all the slices compared to the middle 9 slices for all three classifiers. The accuracy difference, however, was not large except for Resnet50 using the middle 9 slices on the axial plane. The DCNN with Residual Learning approach is the best-performing model, mainly for meniscus tear classification on the sagittal, axial, and coronal planes. This approach can be extended further to develop multi-class classification by considering the severity of knee injuries.

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