2024 First International Conference on Technological Innovations and Advance Computing (TIACOMP) | 979-8-3503-9211-1/24/$31.00 ©2024 IEEE | DOI: 10.1109/TIACOMP64125.2024.00035

A Comprehensive Review of Knee Abnormalities Detection Current Procedures, Outcomes and Prospects

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***Abstract* - Knee joints are made up of cartilage, bone, fluid and ligaments in which muscles and tendons are there for helping knee joints movement. Knee pains caused due to injury, repeated stress on knee or aging. Knee abnormalities or injury can be diagnosed using different methodologies like X-RAY, CT scan, Arthroscopy or MRI. In our survey, we thoroughly analyzed several recent research to investigate the landscape of predictive modeling, a comprehensive analysis of current literature, evaluating trends, and methodologies. We identified that deep-learning models showcased average accuracy for predicting that knee is normal or abnormal is ranged from 63.4% to 98%. In this review paper, we also highlight several limitations like challenges for generalization of models in different centers, biasness in verification, lack of multi-classification studies, unavailability of data and subjectivity of ground-truth. We also proposed An Explainable Attention Based Deep Learning Knee Anomalies Prediction Model with Ensemble Learning Algorithms framework. Here, multi-modal deep learning model architecture is designed to handle and learn from multiple types of data inputs. We achieved 84.54% accuracy with Kaggle knee dataset.**

Index Terms* - *Knee abnormalities, deep learning, diagnostic models, performance metrics..

I. Introduction

Bones, like other organs, are vital and serve a range of functions. When excessive force is applied, bones have the potential to change in size, shrink, get stronger or weaker, and even break. They are one of the few organs in the body that may regenerate after damage without leaving a visible scar. According to National Library of Medicine, human neonates normally have about 270 bones, which fusion results in 206 to 213 bones in an adult.

A knee anomaly is any deviation from the normal anatomy or function of the knee joint. Numerous conditions can harm the bones, cartilage, ligaments, tendons, muscles, and other supporting tissues of the knee joint. A few common knee abnormalities include osteoarthritis, ligament tears, meniscal tears, patellar instability, and chondromalacia patella. Knee abnormalities can cause soreness, edema, stiffness, weakness, instability, and a limited range of motion, among other symptoms. They can be detected using a variety of clinical and radiological tests, and they can also be treated using a combination of prescription medications, physical therapy, and occasionally surgery. "Knee abnormalities" refer to a broad spectrum of diseases that affect the anatomy or operation of the knee joint. For knee analysis, common abnormalities that are targeted include osteoarthritis, anterior cruciate ligament tears, meniscal tears, patellofemoral disorders, etc.

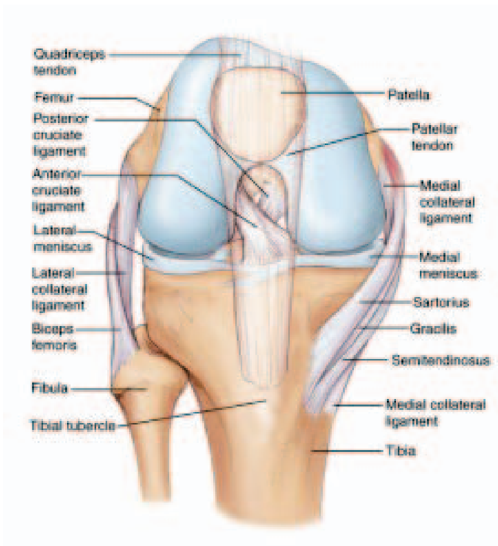

Fig. 1. Knee Anatomy (Source: https://www.ismoc.net/knee.html)

Typically, a medical history, physical examination, and diagnostic testing 1. X-Ray 2. MRI 3. Arthroscopy 4. CT Scan 5. Ultrasound are used to identify knee problems.

II. Literature survey

Deep learning techniques such as convolutional neural networks and recurrent neural networks have shown prodigious ability in analysing medical images and detecting abnormalities. Recent research has explored the applications of deep learning in predicting knee abnormalities using various imaging modalities.

Deep neural networks (DNNs) were used in a study by Sajid Nazir and colleagues on XAI for biomedical imaging predictions detecting and classifying bone fractures from X-ray images. The dataset consists of 100 X-ray images of different types of human bones, including both healthy and

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DOI 10.1109/TIACOMP64125.2024.00035

fractured bones. They used data augmentation techniques like flipping, rotation, shearing etc. are used to expand the small dataset and prevent overfitting. A DCNN model is designed with max pooling layers, convolutional layers, flatten layer and dense layer. Three experiments are conducted using softmax and Adam optimizer, with varying train-test splits. Best accuracy of 95.67% is achieved on 10% test data using Adam optimizer. On 20% test data, Adam optimizer gives 94.67% accuracy. 5-fold cross validation provides an average accuracy of 92.44% across folds. The proposed model outperforms previous methods like ANN (82.98% accuracy) and GLCM+SVM (86.67% accuracy). Key limitations are small dataset size and lack of model interpretation.[1]

As per the view of C. Kokkotis et al., machine learning (ML) applications can be used for diagnosis, prognosis, and therapy planning of knee osteoarthritis (KOA). The authors outlined the present state of ML approaches, such as Bayesian, decision trees, SVM, and ANN, and to find out the development of the disease and novel data-driven tool for early diagnosis and prognosis of knee OA. They explore potential research directions as well as the techniques' merits and limits. They have analyzed the papers and articles from 2006 to 2019 and represented different methodologies used for diagnostic test (MRI, XRay, Demographics, medical data and Kinetic and Kinematic data), feature engineering methods, Learning algorithms, validation methods and model accuracy. The report indicates that imminent study had better emphasis on evolving more accurate and personalized diagnostic and prognosis tools for knee OA using ML. To improve the accuracy of ML models, other sorts of facts, such as imaging, medical and genetic information, could be integrated. The authors also propose that ML can be used to build more adapted treatment plans for knee OA patients, taking individual variables such as age, gender, comorbidities, and lifestyle factors into account. According to them, Support Vector Machine models were the most prevalent across all research categories and convolutional neural networks were examined in research that employed clinical images as inputs. CNN methods were used for feature mining and measuring the sternness of KOA. Additionally, the publication emphasizes the importance of additional research into the interpretability and transparency of ML models in knee OA, in order to ensure that they are understandable and trustworthy for doctors and patients.[2]

Shilpa Sharma et al. used glamorous resonance imaging (MRI) to demonstrate a deep literacy strategy for detecting multiple types of knee injuries. The authors outlined the frequency and consequences of knee injuries, as well as the limits of current individual approaches. They also detailed their suggested system for classifying knee MRIs into four different gash types using the ResNet50 deep literacy model meniscal gashes, ACL gashes, PCL gashes, and MCL gashes. They trained their models in three ways - Using 18 slices, 3 slices and only 1 slice of each MRI sample. They used reviews from three airplanes coronal, axial, and sagittal. Delicacy scores they entered for Abnormal MRIs- 3 slices-91.66, for ACL Gashes – 18 slices –86.66 and for Meniscus Gashes – 3 slices –79.16. Eventually, they suggested in unborn ensemble ways would most probably boost overall performance. likewise, in the future, a multiclassification model that can catalogue an MRI into ACL, abnormal, and meniscus gashes can be established. The position of the excrescence point is critical when using MRI reviews to diagnose malice. [3]

Rabbia Mahum et al. presented a innovative tactic for detecting knee osteoarthritis in primary phases using a combination of deep CNN features and traditional ML algorithms like SVM, Random Forest, and KNN. The 400 – for training and 100- for testing X-ray image were occupied from the Mendeley Dataset. The projected procedure has a 97% accuracy. According to them, radiography and MRI remain the clinical standard, but new modalities like bioimpedance, gait analysis and novel joint-implanted sensors are active areas of research for improved detection of knee OA, especially in early stages. Meanwhile, image analysis and machine learning are enhancing the utility of standard imaging for OA assessment. [4]

An adaptive segmentation method for selecting the best region of interest in knee radiograph texture analysis was published by Bayramoglu et al. The study was designed to explore two primary research questions: 1) the impact of ROI position on texture analysis of the subchondral bone in knee radiographs, and 2) the effectiveness of various texture descriptors in distinguishing between knees with osteoarthritis (OA) and those not affected by OA. This research employed bilateral posterior-anterior knee radiographs drawn from two datasets - the Multicenter Osteoarthritis Study, with 3,644 knee radiographs, and the Osteoarthritis Initiative, which provided 9,012 knee radiographs. The team's methodology involved the detailed study of these radiographs using a fully-automatic process that leveraged adaptive segmentation to pinpoint the utmost enlightening region from the subchondral bone. After that, they identified and contrasted the effectiveness of every ROI insertion strategy and numerous texture descriptors using 5-fold cross validation. To understand the wider applicability of the methodology, models were trained using the Osteoarthritis Initiative dataset and then tested on the largest dataset. They found that the adaptive ROI performs better—up to a 9% increase in AUC—than the commonly used standard ROI. Researchers also found that Original Double Pattern (LBP), with an associated AP of 0.804 (0.786,0.820) and an AUC of 0.840 (0.825,0.852), performed the greatest under all conditions across all textural factors. Limitations exist due to sensitivity to imaging conditions, empirical parameters, simplified bone segmentation, specific landmark detection tool usage, and lack of a more extensive evaluation on severity grades and different datasets. But the study still demonstrates the significant impact of optimal ROI localization in bone texture analysis for OA detection. [5]

The study introduced by Tayyaba Tariq et al. is an fine-tuned DL-based approach to detect knee osteoarthritis (KOA) and grade its severity from X-ray images based on the Kellgren-Lawrence (KL) scale. Utilizing transfer learning and fine-tuning ResNet-34, VGG-19, DenseNet 121, and DenseNet 161, an ensemble model is created to enhance overall performance. Results show promising outcomes with 98% overall accuracy, 0.99 Quadratic Weighted Kappa, and improved accuracy per KL grade. The method surpasses existing automated approaches, offering a quick and reliable evaluation of knee X-rays for medical practitioners, saving valuable time. The ordinal classification approach significantly enhances system performance, and the ensemble model further improves various evaluation metrics. Key limitations are the need for more diverse datasets and potential inter-rater variability in KL grades. [6]

As per the study done by Dea Nurfadhillah et al., the manual detection of osteoarthritis typically relies on the experience and agreement among doctors using the Kellgren Lawrence system. The goal of this research was to develop DenseNet201 to aid doctors in diagnosing and grading osteoarthritis. The study assessed the performance of DenseNet201 by analyzing various metrics, including accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV). A total of 75 knee joint images were used for testing, and the results were compared with classifications made by radiologists. The analysis was performed using the Wilcoxon statistical test. The key results demonstrate decent performance of the DenseNet201 model, with accuracy 91.84%, sensitivity 76.61%, specificity 94.32%, PPV 82.60%, and NPV 94.32%. Importantly, no significant difference was found between the model and radiologist classifications. This indicates the feasibility of using DenseNet201 for automatic knee osteoarthritis grading. Some additions around radiologist grading methodology, visualizations, clinical impact and comparison to literature would further strengthen the paper. [7]

Bruno Astuto and others. Knee ligament (ACL) has developed a deep learning-based methodology for identifying and characterizing abnormalities in knee MRI scans to explore the proposition that AI devices can help for detection and evaluation of tendon, cartilage, meniscus, and anterior cruciate injuries Increases overall MRI-intergrader agreement. A total of 1435 knee MRI scans of 294 patients in which 153 images are of women with the mean age of 43 years were pooled over three prior studies (2011 to 2014) to obtain a high-spatial-resolution three of all MRI scans -dimensional fast -Spin-echo-CUBE sequence was used. A 3D CNN was established to identify provinces of interest in the MRI data and grade cartilage, menisci, bone marrow, and ACL anomalies Double tear sensitivity for all tissues ranged from 70 to 88%. The specificity wavered from 85% to 89%. For all tissues, the area underneath the ROC Curve ranged from 0.83 to 0.93. When applied to an external data set, the three-dimensional muscle elasticity demonstrated excellent sensitivity, specificity, and accuracy for the assessment of acute knee injury, and intraclass agreement it also improves. [8]

An automatic DL-based algorithm for estimating KOA severity was proposed by Joseph Antony and others for knee joint detection with radiographs The authors discussed the proposed method, in which radiographs automatically detect knee joints and measure joint space width (JSW), an important biomarker for severe knee OA Hypothesis and the Multicenter Osteoarthritis Study, with very propitious results beyond existing methods Combined trained correlations for classification and regression provide 63.4% high multiclass classification accuracy and 0.661 minimum mean class error It is suggested that future research knee-OA. To estimate the severity, it finally focuses on training the end-to-end communication network, incorporating FCN for routing and CNN delivery will be divided. [9]

The research paper authored by Meng Xue and his team presented a novel automated deep learning method aimed at detecting knee joint damage caused by combat. The study was conducted over five years, from 2015 to 2020, and involved an extensive data set of knee MRI images from 1546 individuals with varying injuries to their knee joints due to combat circumstances. The collected data was meticulously categorized into six types of injuries: meniscus damage, tendon damage, ligament damage, epiphyseal cartilage damage, and synovial joint capsule loss. By leveraging a deep learning neural network, the team was able to model and differentiate between these types of injuries, accurately identifying the location of the knee joint damage. The researchers ran validation tests on this model, which yielded impressive results: the model was able to accurately identify meniscal injuries at a rate of 83.2%, tendon injuries at 89.0%, ligament injuries at 88.0%, bone and cartilage injuries at 85.9%, and synovial joint capsule injuries at 85.6%. Moreover, the overall accuracy of the model was impressive, measuring at 86% with adequate precision. Sensitivity and specificity of the model were recorded at 91% and 87.3%, respectively. The team improved the conventional U-Net model to enhance the efficiency of training and versioning. This represents a significant advancement over traditional manual labeling techniques. The model demonstrated an average accuracy of 86.0% on a test data set and proved effective in identifying adjacent lesions and differentiating between variations of lesions. The average popularity accuracy of the version was 86.0% in the take a look at data set, and it can effectively identify lesions adjacent to lesions and classify lesion variations, indicating that the version has a utility cost great in pharmacology and deserves further development and research. [10]

According to Abdul Sami Mohammed et al., the current manual diagnosis involves the examination of X-ray of the knee using the Kellgren–Lawrence (KL) system, which categorizes the condition into five grades. However, this manual process demands significant time, expertise, and is prone to errors. This study proposes the use of six DNN models—VGG16, VGG19, MobileNetV2, ResNet101, InceptionResNetV2, and DenseNet121—for diagnosing KOA. The images utilized are sourced from the Osteoarthritis Initiative (OAI) dataset. The classification involves two aspects: binary classification, indicating the presence or absence of KOA, and three-class classification, indicating the severity of KOA. For a comprehensive evaluation, the study conducts experiments on three datasets representing various classes of KOA images. The best performance is achieved by ResNet101, obtaining accuracies of 69%, 83%, 89% on the 3 datasets respectively. [11]

Athanasios Siouras, along with other researchers, has conducted a thorough evaluation of various studies that have used deep learning methods to detect knee injuries through Magnetic Resonance Imaging scans. A total of 407 studies were initially gathered from various sources. However, 37 of these collected studies were then excluded from the review due to the presence of irrelevant data. Considering everything, 22 publications were finally included in the current systematic review. The main objective of this review is to provide a comprehensive overview of the use of deep learning methods in detecting knee injuries, specifically anterior cruciate ligament, meniscus, and cartilage injuries, based on the available literature. The predictive accuracy of the reviewed deep learning models for knee injury detection was found to vary, ranging from 72.5% to 100%. Current DL algorithms have several shortcomings, such as data unevenness, pattern generalizability athwart multiple centers, validation bias, dearth of relevant cataloguing research beyond two classes. Additional concerns include subjectivity in the determination of the ground truth and the diagnosis of knee injuries based on MRI scans. To address these challenges and enhance the effectiveness of these algorithms, various areas have been identified for future research on deep learning. Among these, the need for more transparency and simplicity in the design of deep learning systems is anticipated to be key factors for their widespread adoption in clinical practice. [12]

Tack and his team have established a novel method to identify meniscal tears in MRI data, boasting high performance. This methodology employs a CNN which operates on comprehensive 3-Dimensional MRI data. The procedure they have created perceives meniscal tears in three precise anatomical subregions: the body, anterior horn, and posterior horn for both medial meniscus (MM) and lateral meniscus (LM). Only pertinent information in the RoI regarding the amount of data for tear detection is captured. In total, 2,399 DESS MRI scans obtained from the osteoarthritis hypothesis database were used to test and validate our CNN-based meniscal tear detection approach. In addition, they evaluated the accuracy of the tear detection method and applied their model to mid-IW TSE MRI images to demonstrate that their system is a generalizable Receiver Operating Characteristic (ROC) for two MRI sequences) curves. The detection method produced AUC values of 0.94 for the anterior horn, 0.93 for the body, and 0.93 for the posterior horn in MM, and 0.96, 0.94, 0.91 respectively for LM in DESS MRI. These results are indicative of the high performance of the method. They intend to see if this approach helps doctors in their diagnostic work in the future. [13]

Xiongfeng et al., published a study in which deep learning techniques were used to detect cystic lesions in knee MRI images. From January to October 2021, 282 participants with confirmed knee osteoarthritis were studied at our institution. Stress-based Squeeze-and-Excitation (SE) origins The SE-YOLOv5 model is constructed on a self-reflective approach to identify and distinguish between knee ulcer-like knee lesions and knee fluid interference, all of which magnetic resonance imaging (MRI) images are T2-weighted signal intensity. The initial deep learning model successfully addressed the task of cyst detection in Yolo V5, achieving F1, accuracy, and MAP scores of 0.832, 0.843, and 0.821, correspondingly. Upon integrating the conceptual SE module into the Yolo V5 model architecture, the background concept-landscape model exhibited a remarkable improvement in the F1 score. Additionally, the chart demonstrated the independence and significant limitations of the manual model, which exhibited commendable smoothness and forward speed with scores of 0.879, 0.87, and 0.944. First, Baker’s excrescence, meniscal excrescence, and intraosseous excrescence are present in cruciate ligament insertion, but these colorful tubercle subtypes were not precisely defined in this study. Second, their data set was small, and model performance was inconsistent with mortality intentions. Additionally, the classification of abnormalities based on reports or prints was conducted smoothly, but the absence of standardized criteria for identifying natural effusions could pose a limitation for the model, as well as for radiologists and ground truth markers. Finally, it is crucial to acknowledge the model's limitations and interpretability, and further evaluate its performance using external or public datasets. [14]

Imran Iqbal and others have proposed a DL based model for the exposure of synovial fluid in the humanoid knee joint using MRI. They developed special CNN based architecture which automatically detect synovial fluid in the human knee joint. The proposed model is trained, developed, and tested using two different datasets. DICOM files were collected from Shanghai Main Laboratory orthopedic implants for training and DICOM files for development and testing setup were obtained from PC Hospital Liaoning with a total of 17,196 images of which 1433 original images and image with 15,763 reinforcements for training the proposed Model achieved an overall accuracy of 86.77%. Before implementing this model full in clinical practice, further investigation is required. [15]

Research done by Ahmet Ezgi et al. focuses on knee osteoarthritis (OA), a common joint problem that needs accurate evaluation for proper treatment. They have created a computerized system using advanced technology called deep neural networks to grade how severe knee osteoarthritis is. Their exploration involves various network setups like VGG-16, VGG-19, ResNet-101, EfficientNet-B7, and EfficientNet-B6. They scrutinized different optimization methods like SGD, ADAM, Nadam, AdamW, and AdaDelta, along with two loss functions: the novel ordinal loss and cross-entropy loss. After careful testing, they discovered that using a combination of EfficientNet-B7 and Nadam gives the most accurate results, achieving a 70.1% accuracy in grading the severity of knee osteoarthritis. This shows that advanced computer systems can help doctors and researchers better manage knee osteoarthritis. Certain limitations are there - such as single dataset evaluation, generalizability to new datasets, model uncertainty, etc. [16]

Kim et al. introduced a novel automated approach utilizing a deep learning algorithm to identify invasive surgery in plain knee radiographs. The primary objective of this research was to develop a deep learning system capable of detecting 17 distinct surgical implants in plain knee radiographs. The dataset consisted of 5206 anterior and posterior x-rays of unrepaired knees obtained from a single university, while an additional set of 238 x-rays from a different university formed the outer group. The registered implants encompassed various types, including total knee arthroplasties, segmented knee arthroplasties, and plates and screws. The evaluation grid employed for this study was You Only Look Once (YOLO). The validation set, internal test set, and external test set exhibited specificity, sensitivity, and specificity values of (0.978, 0.768, 0.999), (0.953, 0.810, 0.990), and (0.956, 0.493, 0.975), correspondingly. This method has several limitations such as: First, the internal data used in the study had a class imbalance issue, including total knee joints a large proportion of totally generated (TKA) data, so that objective evaluation of deep learning (DL) models is challenging and this issue can be mitigated in part by consuming more diverse external data use to conduct the research. Secondly, the DL model exhibited poor sensitivity towards several physiological parameters, underscoring the necessity for further investigation to enhance the model's sensitivity towards these specific implants. Finally, the study used default hyperparameters for model training, which can enhance the performance of models as predictive hyper-parameters. [17]

The study done by Ganesh Kumar M and Agam Das Goswami employs deep CNN in unification with the KL grading system to evaluate the severity of KOA. As per their study to use machine and deep learning for knee osteoarthritis have faced challenges, particularly due to inadequate preprocessing of images. This resulted in suboptimal feature extraction by deep learning models, affecting overall performance. With enhanced images using the image sharpening process, the study achieved 91.03% mean accuracy. The image sharpening technique proves instrumental in advancing knee joint recognition and KL grading, enhancing the precision of osteoarthritis detection. [18]

III. PROPOSED FRAMEWORK

Based on the findings, we observed that techniques like data augmentation, transfer learning, adversarial training, and attention mechanisms have been incorporated. But further research is required to make the models robust and deployable in clinics. Here is the proposed framework for An Explainable Attention Based Deep Learning Knee Anomalies Prediction Model with Ensemble Learning Algorithm: The proposed framework incorporates data augmentation, transfer learning, adversarial training, and attention mechanisms to develop a robust and deployable deep learning model for predicting knee anomalies. The following detailed explanations cover the tools, frameworks, parameter settings, training procedures, model configurations, hyperparameters, and evaluation metrics used in this framework.

Model Architecture:

1. Define a multi-modal deep learning model architecture.
2. Input layers for Modality 1 Modality 2, and Modality 3. (Diversed multimodal datasets)
3. Convolutional layers for feature extraction from each modality.
4. Fusion or attention mechanisms to combine features.
5. Additional layers for learning higher-level abstractions.
6. Binary classification using signmod activation in output layer.

In this proposed architecture, Modality 1, Modality 2, Modality 3 are the input layers corresponds to a different type of data (e.g., MRI images, X-rays, and clinical data). These input layers handle the diversified multimodal datasets, each with specific preprocessing steps. Separate convolutional layers are designed for each modality to extract relevant features. The typical configuration might involve multiple convolutional blocks, each consisting of convolutional layers followed by batch normalization, ReLU activation, and max-pooling. Self-attention layers or attention modules (e.g., Multi-Head Attention from the Transformer architecture) are used to combine features from different modalities effectively. Fully connected layers or concatenation operations to integrate features from each modality. Dense layers for learning higher-level abstractions, possibly with dropout for regularization. A binary classification layer with signmod activation, suitable for distinguishing between normal and abnormal knees.

Dataset : The dataset consists of 1650 (Normal [514], Doubtful [477], Mild[232], Moderate[221], Severe[206]) digital X-ray images of knee joint which are collected from well reputed hospitals and diagnostic centres. The X-ray images are acquired using PROTEC PRS 500E X-ray machine. Original images are 8-bit grayscale image.

Source : https://www.kaggle.com/datasets/tommyngx/digital-knee-xray/data

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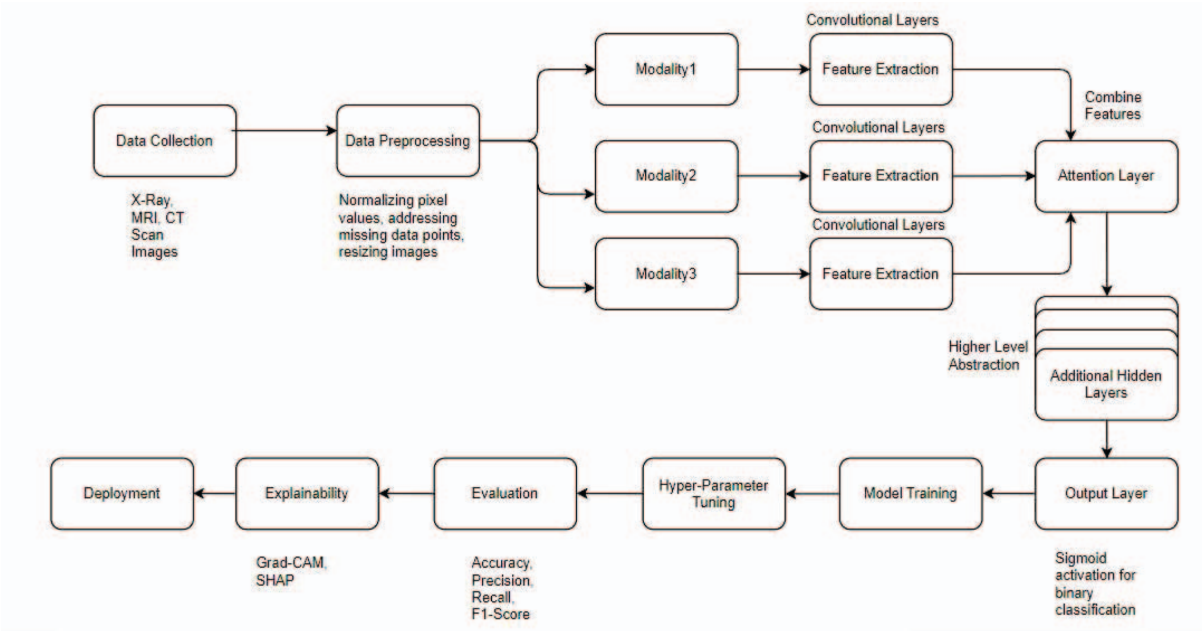

Fig. 2. Proposed Framework

Confusion Matrix for Binary Classification:

To simplify the confusion matrix, we will assume a binary classification task where the objective is to distinguish between normal (class 0) and abnormal (class 1) knees. Here's how the classes are mapped for this binary classification:

Normal (514 images): Class 0
Doubtful, Mild, Moderate, Severe (1136 images): Class 1

True Positives (TP): 771(abnormal knees correctly predicted as abnormal)
True Negatives (TN): 625 (normal knees correctly predicted as normal) False Positives (FP):
104 (normal knees incorrectly predicted as abnormal)
False Negatives (FN): 150 (abnormal knees incorrectly predicted as normal)

	Predicted Abnormal	Predicted Normal
Actual Abnormal	771	150
Actual Normal	104	625

Table 1 ; Confusion Matrix

With this dataset, we achieved : Accuracy: 84.54%, Precision : 88.14%, Recall(sensitivity) : 83.73%, F1-Score : 85.88%

IV. CONCLUSION AND FUTURE WORK

By reviewing various research papers, we identified variety of data sources used, especially medical images, biomechanics and clinical data. SVM and ensemble methods like random forest frequently used with good accuracy. Feature engineering is important for model performance. Several studies have developed CNN models for classifying knee x-rays as normal or abnormal. Pre-trained networks like VGGNet and ResNet are commonly used as feature extractors. Fine-tuning them on knee radiographs has achieved high accuracy for osteoarthritis and fracture detection. Other works have detected cartilage lesions and meniscal tears from knee MRI scans using CNNs combined with region proposal networks. 3D CNN architectures have also been proposed to utilize volumetric

MRI data for diagnosis. RNNs and long short-term memory networks have shown good results in predicting the progression and severity of knee osteoarthritis from longitudinal patient data. Multimodal deep learning methods that combine x-ray, MRI, and clinical data have also been explored for improving diagnosis compared to using any single modality.

Deep learning shows huge potential in knee abnormality prediction but overcoming real-world challenges is vital for clinical integration and impact. The literature highlights active innovation in algorithms, data, and evaluation toward this goal.

In this review paper, we also highlighted several limitations like challenges for generalization of models in different centers, biasness in verification, lack of multi-classification studies, unavailability of data and subjectivity of ground-truth. The proposed framework integrates advanced techniques to build a robust and explainable deep learning model for knee anomalies prediction. By leveraging multimodal data, attention mechanisms, and ensemble learning, the model aims to provide accurate and reliable predictions suitable for clinical deployment. Limitation of our research is right now we implemented modal only with knee x-ray images. Digital X-ray images are often the primary diagnostic tool for knee abnormalities and provide rich visual information about bone structure, alignment, and potential abnormalities. X-ray images are readily available and commonly used in clinical practice, making them a practical starting point for model development. In future, we will integrate additional modalities to enhance its predictive capability We will also check ethical and clinical implementation of our model and its validity and viability too.

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