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Knee Osteoarthritis Detection Using X-ray Images

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Abstract: Knee osteoarthritis stands out as a prevalent form of arthritis, characterized by joint space reduction, osteophyte emergence, sclerosis, and bone distortion, which are observable through radiographs. Radiography stands as the benchmark and the most accessible and cost-effective modality. X-ray images are assessed based on the Kellgren and Lawrence grading system, which ranks osteoarthritis severity from normal to severe. Early identification is crucial for prompt intervention and slowing down knee osteoarthritis progression. Unfortunately, many current methods either combine or exclude complex grades to enhance model performance. This study aims to automatically detect and categorize knee osteoarthritis in line with the KL grading system for radiographs. We propose an automated deep learning-based ordinal classification approach for early detection and grading of knee OA using a single posteroanterior standing knee x-ray image.

Keywords: Knee osteoarthritis, Radiography, Deep learning, Ordinal classification, Transfer learning, Ensemble model, Kellgren and Lawrence grading system.

I. INTRODUCTION

Osteoarthritis of the knee is a common chronic degenerative joint disease marked by changes in the subchondral bone inflammation of the synovium and degeneration of articular cartilage. It affects millions of individuals worldwide, causing pain, stiffness, and functional impairment, thereby significantly reducing the feature of life for those afflicted. Early detection and intervention are crucial to mitigate the progression of the disease and improve patient outcomes.

The majority of traditional knee OA diagnosis techniques focus on clinical assessment which includes X-Rays,physical examinations patient-reported symptoms, radiographic imaging. While X-ray imaging remains the gold standard for OA diagnosis due to its accessibility and cost-effectiveness, its interpretation is subjective and reliant on the expertise of radiologists. This subjectivity often leads to inter-observer variability and delays in diagnosis, hindering timely intervention and management.

To address these challenges, analysts and clinicians have progressively turned to computer-aided determination (CAD) frameworks leveraging machine learning (ML) and picture preparing methods. These frameworks point to mechanize the location and classification of knee OA from X-ray pictures, advertising objective, reproducible, and effective demonstrative back.

In this paper, we display a novel approach for robotized knee OA location utilizing X-ray imaging. Our proposed framework coordinating progressed ML calculations with state-of-the-art picture handling methods to analyze radiographic highlights characteristic of OA pathology. By preparing our show on a huge dataset of commented on X-ray pictures, we point to create a vigorous and exact CAD framework able of recognizing early signs of knee OA with tall affectability and specificity. The essential goals of this inquire about incorporate:

1. Designing a deep learning architecture tailored for knee OA detection from X-ray images.

2. Extracting and analyzing relevant radiographic features associated with knee OA progression.

3. Evaluating the performance of the proposed CAD system against existing diagnostic methods, including radiologist interpretation.

4. Investigating the clinical utility and potential impact of the CAD system on patient care pathways and outcomes.

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Through this, we envision a paradigm shift in the diagnosis and management of knee OA, wherein automated CAD systems complement traditional approaches to enhance diagnostic accuracy, reduce interpretation variability, and facilitate timely interventions, ultimately improving patient prognosis and quality of life.

II. MATERIALS AND METHODOLOGY

MATERIALS:

1. X-ray Image Dataset: Obtain access to a comprehensive dataset of knee X-ray images, preferably sourced from established repositories like the Osteoarthritis Initiative (OAI) dataset. Ensure the dataset includes a sufficient number of images covering various stages of knee osteoarthritis, graded according to standardized protocols such as the Kellgren-Lawrence (KL) grading scheme.

2. Image Preprocessing Tools: Utilize software libraries such as OpenCV or PyTorch to preprocess X-ray images before feeding them into the detection model. Common preprocessing steps include resizing, normalization, and noise reduction to enhance image quality and facilitate accurate feature extraction.

3. Convolutional Neural Network (CNN) Framework: Implement a CNN-based architecture tailored for knee osteoarthritis detection. Popular frameworks like TensorFlow or PyTorch provide a robust foundation for building and training deep learning models. Leverage established architectures such as ResNet, DenseNet, or custom-designed networks optimized for medical image analysis tasks.

4. Transfer Learning Pre-trained Models: Access pre-trained CNN models, preferably trained on large-scale image datasets like ImageNet. Fine-tune these models using knee X-ray images to leverage their learned features and accelerate training convergence. Transfer learning aids in overcoming data scarcity issues and enhances the generalization capability of the detection model.

5. Annotation Tools: Employ annotation tools such as LabelImg or VGG Image Annotator to annotate X-ray images with ground truth labels, indicating the presence and severity of osteoarthritic changes. Ensure annotations align with established grading systems to facilitate model training and evaluation.

6. Computational Resources: Secure access to computational resources such as GPUs or TPUs to expedite model training and evaluation processes. High-performance computing platforms or cloud-based services like Google Colab offer scalable infrastructure for conducting intensive deep learning experiments.

7. Evaluation Metrics: Set up appropriate evaluation criteria to fair-mindedly assess the location model's execution. Exactness, accuracy, review, F1-score, and region beneath the recipient working characteristic bend (AUC-ROC) are common measures for twofold classification errands. Make beyond any doubt measures take clinical significance and lesson awkwardness into consideration when diagnosing OA within the knee.

8. Research Papers and Literature: Review existing research papers and literature on knee osteoarthritis detection using X-ray images to gain insights into established methodologies, challenges, and state-of-the-art approaches. Identify relevant studies for benchmarking and compare the performance of the proposed detection model against existing methods.

9. Ethical Considerations: Adhere to ethical guidelines and regulations governing the use of medical data and patient information. Obtain necessary approvals from institutional review boards (IRBs) and ensure compliance with data protection laws to safeguard patient privacy and confidentiality throughout the research process.

10. Documentation and Reporting: Document the research methodology, experimental setup, and results comprehensively to ensure reproducibility and transparency. Prepare a detailed research paper adhering to the guidelines of reputable scientific journals, highlighting the novelty, significance, and implications of the proposed knee osteoarthritis detection approach.

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Methodology:

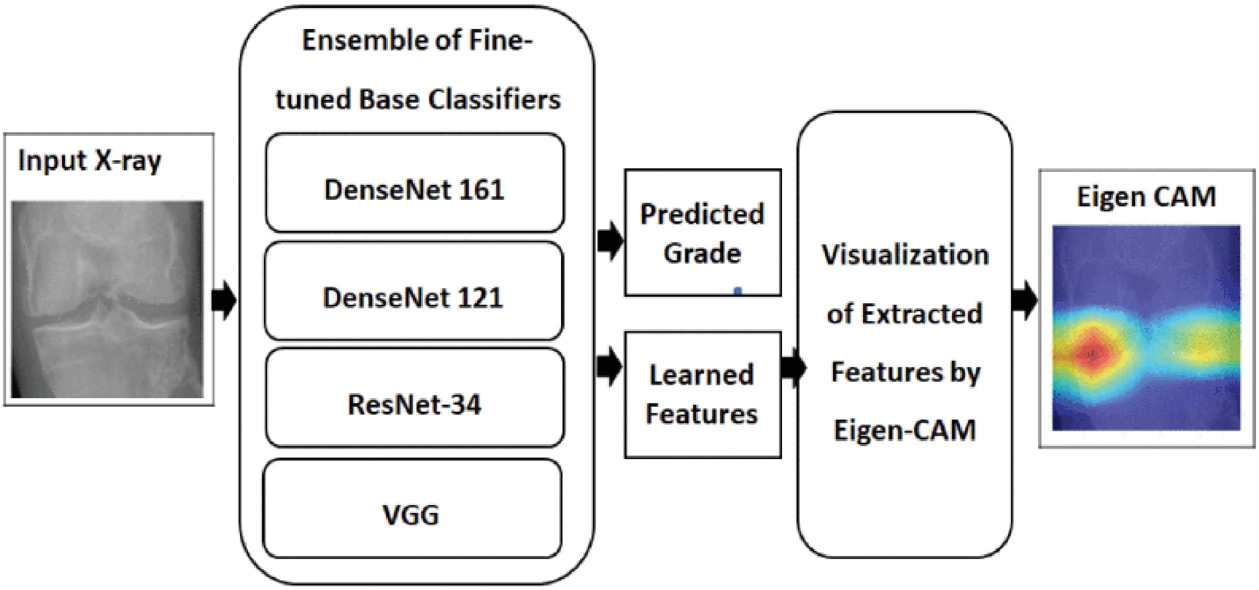

Fig. 1: Knee Osteoarthritis Classification

Dataset Overview: The dataset utilized in this think about begins from the Osteoarthritis Activity dataset, comprising a add up to of 9786 X-ray pictures. Each picture is reviewed agreeing to the KL evaluating plot, with the taking after conveyance:3857 pictures reviewed as 0, 1770 as review 1, 2578 as review 2, 1286 as review 3, and 295 as review 4. All pictures inside the dataset are standardized to a settled estimate of 224×224 pixels. One eminent characteristic of the dataset is its characteristic lesson awkwardness.

To address this issue, a stratified part procedure is utilized, partitioning the information into unmistakable preparing, testing, and approval sets. This stratification guarantees that each subset keeps up a corresponding representation of tests from each reviewing category. The conveyance of information over the preparing, testing, and approval sets is visualized in Figure 2, showing the adequacy of the dividing approach in keeping up course adjust. This dividing strategy is reliable with past thinks about, illustrating its unwavering quality and reproducibility in comparable investigations.

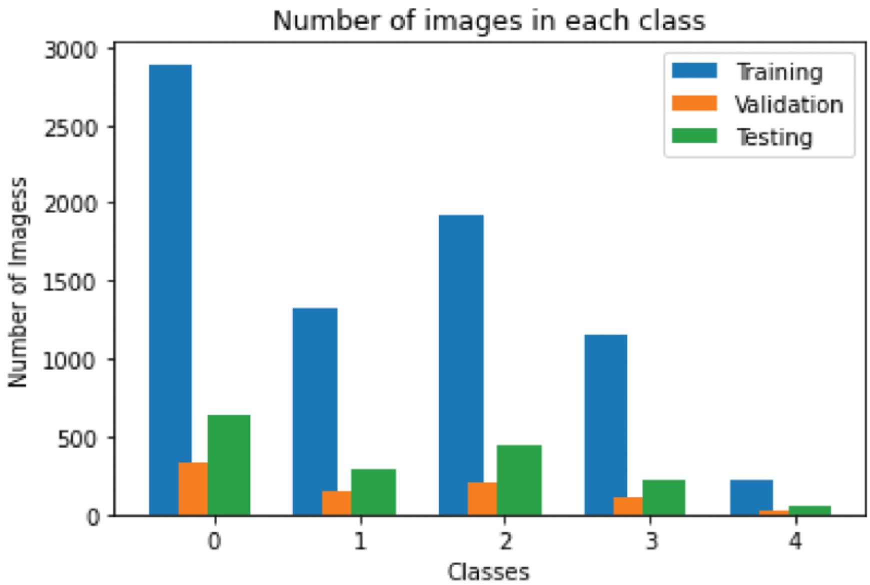

Fig. 2: Number of images

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Networks for Knee Osteoarthritis Detection: Within the domain of knee osteoarthritis location utilizing X-ray pictures, different arrange models have been created to encourage precise and productive conclusion. Convolutional Neural Systems (CNNs) stand out as a overwhelming choice due to their capacity to consequently extricate pertinent highlights from picture information. These systems use various leveled layers of convolutional channels to continuously learn complicated designs and structures inside X-ray pictures, empowering them to observe unpretentious signs of osteoarthritis. One commonly utilized engineering is the Remaining Arrange (ResNet), famous for its profound structure and lightening of vanishing angle issues. ResNet's remaining associations permit for the consistent stream of data through the organize, empowering the viable capture of both low-level and high-level highlights vital for knee osteoarthritis location. By leveraging leftover squares, ResNet structures accomplish exceptional execution indeed with altogether more profound systems, hence improving the precision of symptomatic forecasts.

In addition, Thick Convolutional Systems (DenseNet) offer another promising approach for knee osteoarthritis discovery. DenseNet's thick network design cultivates include reuse over layers, advancing include proliferation and improving data stream all through the organize. This design is especially invaluable in scenarios with restricted information, because it encourages effective parameter utilization and fortifies highlight representation, eventually driving to made strides discovery accuracy. Additionally,attention mechanisms have developed as a important improvement in knee osteoarthritis location systems. These instruments empower systems to center on important locales inside X-ray pictures, viably distributing computational assets to zones showing potential markers of osteoarthritis. By joining consideration instruments, systems can prioritize notable highlights, subsequently making strides both exactness and interpretability of symptomatic results. Moreover, exchange learning methodologies have been broadly embraced within the advancement of knee osteoarthritis discovery systems. Pre-trained CNN models, such as those prepared on large-scale picture datasets like ImageNet, are fine- tuned utilizing knee X-ray pictures to adjust the network's parameters to the particular errand of osteoarthritis location. This approach quickens demonstrate meeting and improves execution, particularly in scenarios with restricted clarified information.

In rundown, the improvement of neural arrange designs custom fitted for knee osteoarthritis discovery utilizing X-ray pictures has essentially progressed demonstrative capabilities. Leveraging the qualities of CNNs, consideration components, and exchange learning, these systems illustrate momentous viability in precisely distinguishing and characterizing osteoarthritic changes, subsequently contributing to progressed clinical decision-making and quiet care.

Experiments for Knee Osteoarthritis Detection:

1) Base Classifiers:

a. Logistic Regression: Execute calculated relapse as a pattern classifier for knee osteoarthritis location. Assess its execution in terms of precision, exactness, review, and F1-score to set up a benchmark for comparison with more complex models.

b. Support Vector Machine (SVM): Explore SVM classifiers with linear, polynomial, and radial basis function (RBF) kernels to capture nonlinear relationships in knee X-ray images. Assess the impact of kernel selection and regularization parameters on model performance.

c. Decision Trees: Construct decision tree classifiers to capture hierarchical relationships between image features and osteoarthritic severity levels. Experiment with tree pruning techniques and tree depth constraints to prevent overfitting and improve generalization.

d. k-Nearest Neighbors (k-NN): Utilize k-NN classifiers to classify knee X-ray pictures based on the closeness of include vectors. Examine the impact of distinctive separate measurement (e.g., Euclidean, Manhattan) and the number of neighbors(k) on classification exactness.

e. Random Forest: Employ random forest classifiers to leverage the ensemble of decision trees for knee osteoarthritis detection. Evaluate the impact of tree ensemble size, feature subset size, and bootstrap sampling on model robustness and performance.

f. Naive Bayes: Implement Naive Bayes classifiers assuming independence among image features to classify knee X- ray images. Assess the suitability of the Naive Bayes assumption and its impact on classification accuracy compared to more sophisticated models.

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2) Ensemble:

a. Voting Classifier: Construct ensemble classifiers using a combination of base classifiers (e.g., logistic regression, SVM, decision trees) through majority voting or weighted voting schemes. Investigate the diversity of base classifiers and their contribution to ensemble performance.

b. Bagging (Bootstrap Aggregating): Apply bagging technique to prepare numerous base classifiers on bootstrap tests of the preparing dataset. Total person classifier forecasts to create the ultimate gathering expectation, relieving overfitting and upgrading show strength.

c. Boosting (AdaBoost, Gradient Boosting): Investigate boosting calculations such as AdaBoost and angle boosting to successively prepare base classifiers, centering on misclassified occasions. Survey the affect of boosting emphasis and learning rates on gathering joining and classification precision.

d. Stacking (Stacked Generalization): Implement stacking as a meta-learning technique to combine predictions from diverse base classifiers using a higher-level meta-classifier. Experiment with different meta-classifiers (e.g., logistic regression, SVM) and stacking architectures to optimize ensemble performance.

e. Ensemble Pruning and Selection: Employ techniques such as ensemble pruning and selection to identify and retain the most informative base classifiers while discarding redundant or poorly performing ones. Evaluate the trade-off between ensemble complexity and performance improvement in knee osteoarthritis detection.

f. Cross-Validation and Performance Evaluation: Validate ensemble classifiers using cross-validation techniques to estimate their generalization performance. Compare ensemble classifiers with individual base classifiers and assess their effectiveness in improving classification accuracy and robustness for knee osteoarthritis detection.

Evaluation Metrics:
In evaluating knee osteoarthritis detection models using X-ray images, a comprehensive suite of evaluation metrics is essential for assessing their accuracy, robustness, and clinical relevance. These metrics serve to quantify the models' performance in accurately classifying X-ray images and identifying osteoarthritic changes. Accuracy, as a fundamental metric, measures the proportion of correctly classified images, providing an overall indicator of model correctness across both healthy and osteoarthritic knees. Exactitude and recollect offer insights into the model's ability to avoid false positives and capture all instances of osteoarthritis, respectively.

The F1-score, a consonant cruel of exactness and review, gives a adjusted appraisal of demonstrate execution, especially profitable for imbalanced datasets. The Zone Beneath the Recipient Working Characteristic Bend (AUC-ROC) comprehensively summarizes the model's segregation capacity over different edges .Additionally, the confusion matrix offers a detailed breakdown of the model's predictions compared to ground truth labels, revealing the types of classification errors made. Sensitivity analysis assesses the model's robustness to variations in data or parameters, crucial for real-world applicability. Interpretability metrics provide insights into the model's decision-making process, enhancing its clinical interpretability. Finally, cross-validation scores offer estimates of the model's generalization performance, mitigating overfitting risks and providing reliable performance estimates. Collectively, these evaluation metrics form a robust framework for assessing knee osteoarthritis detection models' performance, facilitating model comparison, parameter optimization, and validation of clinical utility.

III. RELATED WORKS

An approach by Anifah et al. utilized Differentiate Restricted Versatile Histogram Equalization and Layout coordinating for Knee Osteoarthritis (KOA) reviewing. They accomplished a classification exactness of 93.8% for KL review 0, 70% for KL review 1, 4% for KL review 2, 10% for KL review 3, and 88.9% for KL review 4. Chen et al. employed the YOLO2 Network for fully automated knee joint detection and tested various fine-tuned networks including ResNet, VGG, and DenseNet. Their highest accuracy reached 69.7%, with a Mean Absolute Error of 0.344. Thomas et al. developed a CNN-based model for knee Osteoarthritis severity grading from radiographs, achieving an exactness of 0.71 and an F1 score of 0.70. Another study implemented ResNet with Convolution Block attention Module (CBAM), reporting an accuracy of 74.81%, Mean Squared Error (MSE) of 0.36, and Quadratic kappa score of 0.88. Additionally, they observed that KL grade 2 posed the greatest challenge for prediction. Another study evaluated DL model predictions for KOA severity, using a private dataset and achieving AUCs ranging from 0.91 to 0.96 with only imaging data and from 0.97 to 0.95 with both imaging and patient information.

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In another approach, U-Net was used for knee joint localization, achieving sensitivity results for OA levels ranging from 68.9% to 86.0% and specificity results ranging from 83.8% to 99.1%.

Furthermore, they observed variability in inter-observer reliability for KL classification, with misclassifications mainly occurring between adjacent KL grades. Lastly, a transfer learning-based approach using pre-trained ResNet-34 architecture predicted KL grade and OA progression with achieved AUCs ranging from 0.80 to 0.99.

IV. SYSTEM DESIGN

Architecture Diagram:

The architecture diagram serves as a visual roadmap, outlining the structure and workflow of the knee osteoarthritis (OA) detection system. It delineates the primary modules involved in the detection process, elucidating their roles and interactions. The framework starts with the input module, where knee X-ray picture information is presented. Along these lines, the preprocessing module attempts fundamental assignments such as picture resizing and normalization to standardize the input pictures for encourage examination.

Taking after preprocessing, the include extraction module comes into play, perceiving related highlights from the pictures that are characteristic of osteoarthritic changes. These extricated highlights are at that point nourished into the classification demonstrate, leveraging machine learning or profound learning methods to classify the pictures as either solid or demonstrative of OA.

Post-classification, the assessment measurements module assesses the model's execution utilizing different measurements such as exactness, exactness, and review. At long last, the symptomatic report module synthesizes the classification comes about into a comprehensive report, giving bits of knowledge into the nearness or nonattendance of OA within the knee joint based on X-ray picture investigation.

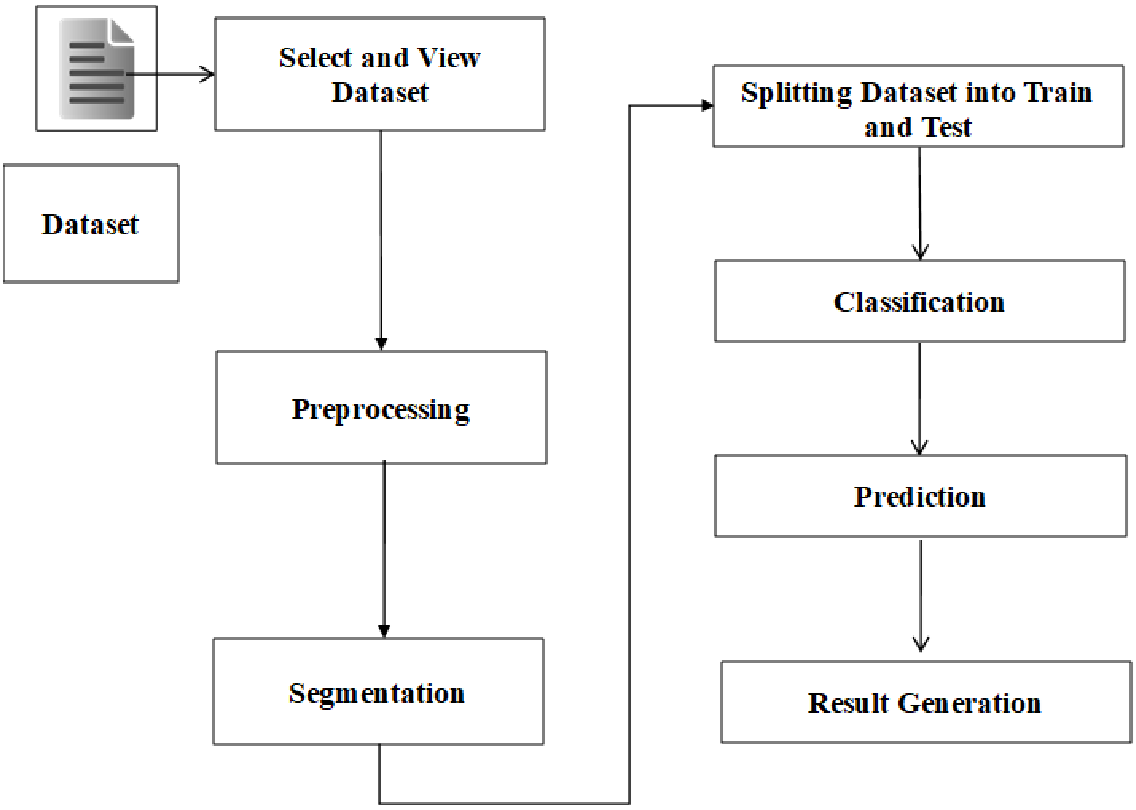

Fig. 3: Architecture Diagram

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Flow Diagram:

The flow diagram offers a visual representation of the orderly movement of information and operations inside the knee OA discovery framework. It outlines the successive execution of assignments embraced by each module, coordinating a coherent workflow from picture input to demonstrative report era. Starting with the input module, knee X-ray picture information is handled through progressive stages, with each module performing particular capacities to refine and analyze the input information.

The bolts within the graph signify the directional stream of data between modules, illustrating the efficient exchange of information from one preparing arrange to the another. This chart serves as a diagram for understanding the step-by-step handle included in knee OA location utilizing X-ray pictures, encouraging a all encompassing see of the system's operational elements.

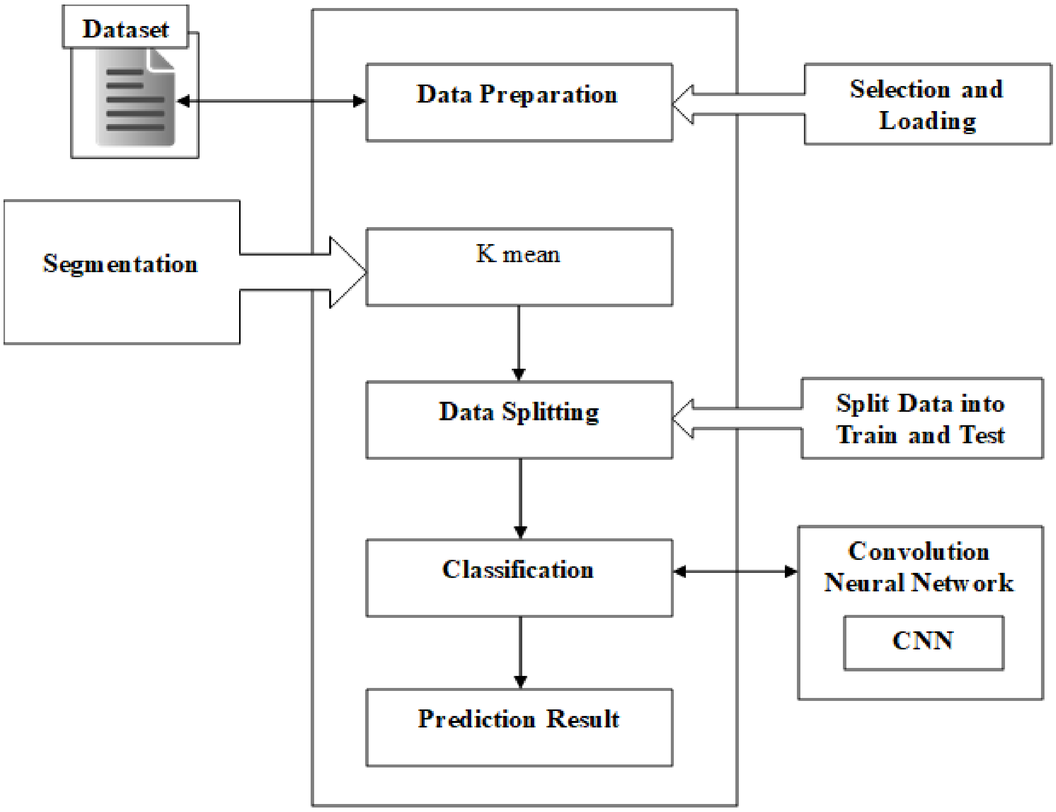

Fig. 4: Flow Diagram

UML Diagrams:

The UML graphs give a graphical representation of the classes and their affiliations inside the knee OA discovery framework. Each lesson typifies a particular component or module inside the framework, encapsulating its qualities and behaviors. The connections between classes depict the stream of information and control between diverse framework components, enlightening the auxiliary and useful angles of the framework.

These graphs serve as building outlines, directing the plan and execution of the knee OA discovery framework. By outwardly delineating the system's composition and intelligent, UML charts encourage communication among partners and streamline the improvement handle. Besides, they empower designers to conceptualize the system's engineering, distinguish potential plan blemishes, and iteratively refine the framework plan to meet wanted targets .

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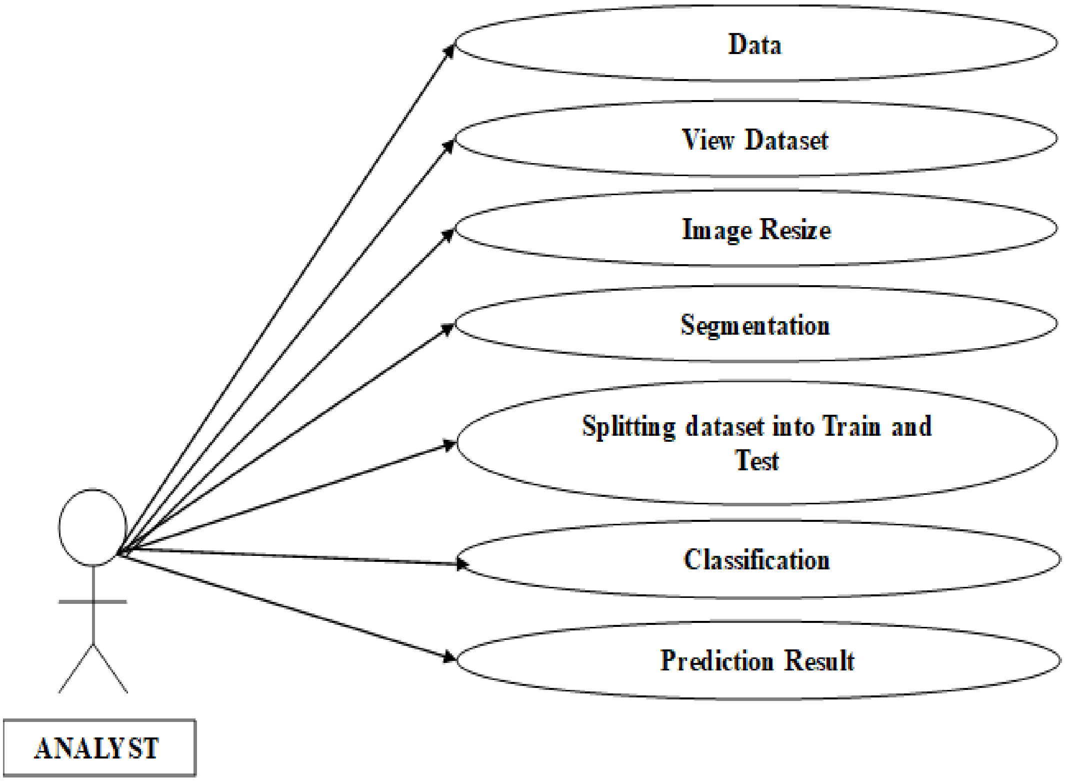

Fig. 5: UML Diagram

V. APPLICATION

The applications of knee OA detection using X-ray images are manifold, offering significant contributions to both clinical practice and medical research. In the realm of clinical diagnostics, these detection techniques serve as invaluable tools for early identification and intervention in knee joint degeneration, enabling healthcare professionals to initiate timely treatment strategies and alleviate patient discomfort. Furthermore, the non-invasive nature of X-ray imaging makes it a preferred modality for routine screening and monitoring of knee OA progression, offering insights into disease severity and guiding personalized treatment plans. Past clinical settings, inquire about endeavors in this space clear the way for progressions in restorative imaging innovation and machine learning calculations, encouraging the improvement of mechanized location frameworks able of precisely diagnosing knee OA from X-ray pictures with tall affectability and specificity. Such developments hold guarantee for progressing healthcare openness and reasonableness, especially in resource-constrained locales where master radiologists may be rare. In addition, collaborative endeavors between clinicians, analysts, and industry partners cultivate intrigue information trade and drive advancement in knee OA location strategies, eventually upgrading understanding results and quality of life. Hence, the applications of knee osteoarthritis discovery utilizing X-ray pictures expand distant past clinical determination, including a range of investigate, innovative, and societal suggestions that contribute to the progression of healthcare hones and patient-centric care.

VI. CONCLUSION

In conclusion, the utilization of X-ray pictures for knee osteoarthritis (OA) discovery speaks to a transformative headway in restorative imaging innovation, advertising significant suggestions for both clinical conclusion and inquire about advancement. Through the integration of sophisticated machine learning algorithms and image processing techniques, these methodologies enable healthcare professionals to accurately identify and monitor the progression of knee OA, facilitating early intervention and personalized treatment strategies. Moreover, the non-invasive nature of X-ray imaging makes it a cost-effective and widely accessible modality for routine screening and assessment, enhancing healthcare accessibility and affordability. Besides, collaborative inquire about endeavors in this space cultivate intrigue information trade and drive development, clearing the way for the improvement of robotized discovery frameworks with tall affectability and specificity.

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As such, the applications of knee OA detection using X-ray images extend far beyond clinical practice, encompassing a spectrum of technological, societal, and research implications that contribute to the advancement of healthcare practices and patient-centric care. Moving forward, continued investment in research and technology development holds promise for further improving the accuracy, efficiency, and accessibility of knee OA detection methodologies, ultimately enhancing patient outcomes and quality of life.

REFERENCES

[1]. A. Cui, H. Li, D. Wang, J. Zhong, Y. Chen, and H. Lu, “Global, regional prevalence, incidence and risk factors of knee osteoarthritis in population-based studies,” *EClinicalMedicine*, vol. 29-30, 2020.

[2]. M. T. Mardini, S. Nerella, M. Kheirkhahan et al., “The temporal relationship between Ecological pain and life-space Mobility in Older Adults with knee osteoarthritis: a Smartwatch-based demonstration study,” *JMIR Mhealth Uhealth*, vol. 9, no. 1, Article ID e19609, 2021.

[3]. M. van Smeden, J. B. Reitsma, R. D. Riley, G. S. Collins, and K. G. M. Moons, “Clinical prediction models: diagnosis versus prognosis,” *Journal of Clinical Epidemiology*, vol. 132, pp. 142–145, 2021.

[4]. Roy S., Meena T., Lim S.-J. Demystifying supervised learning in healthcare 4.0: A new reality of transforming diagnostic medicine. *Diagnostics.* 2022;12:2549. doi: 10.3390/diagnostics12102549.

[5]. Alejandro Guerra-Manzanares a, Jorge Medina-Galindo, Hayretdin Bahsi b and Sven Nomm detection of Knee fractures using image processing techniques and artificial neural networks 2021.

[6]. Lee L.S., Chan P.K., Wen C., Fung W.C., Cheung A., Chan V.W.K., Chiu K.Y. Artificial intelligence in diagnosis of knee osteoarthritis and prediction of arthroplasty outcomes: A review. *Arthroplasty.* 2022;4:16. doi: 10.1186/s42836-022-00118-7.

[7]. Bayramoglu N., Nieminen M.T., Saarakkala S. Machine learning based texture analysis of patella from X-rays for detecting patellofemoral osteoarthritis. *Int. J. Med. Inform.* 2022;157:104627. doi: 10.1016/j.ijmedinf.2021.104627.

[8]. Teo J.C., Khairuddin I.M., Razman M.A.M., Majeed A.P.A., Isa W.H.M. Automated Detection of Knee Cartilage Region in X-ray Image. *Mekatronika.* 2022;4:104–109. doi: 10.15282/mekatronika.v4i1.8627.

[9]. Tan J.-S., Tippaya S., Binnie T., Davey P., Napier K., Caneiro J.P., Kent P., Smith A., O’Sullivan P., Campbell A. Predicting Knee Joint Kinematics from Wearable Sensor Data in People with Knee Osteoarthritis and Clinical Considerations for Future Machine Learning Models. *Sensors.* 2022;22:446. doi: 10.3390/s22020446.

