A project report on

KNEE OSTEOARTHRITIS ANALYSIS USING MACHINE LEARNING

submitted in partial fulfillment of the requirements for the degree of

B. Tech
In
Electronics and Computer Science Engineering

By

RATAN KUMAR	**2130127**
SIVAKUMAR REDDYMALLA	**2130137**
SIYARAM KUMAR	**2130139**
GAURAV NAYAN	**2130164**

under the guidance of

Prof. Manoj Kumar Parida

School of Electronics Engineering
KALINGA INSTITUTE OF INDUSTRIAL TECHNOLOGY
(Deemed to be University)
BHUBANESWAR

CERTIFICATE

This is to certify that the project report entitled **"Project Title"** submitted by

RATAN KUMAR	**Roll No.2130127**
SIVAKUMAR REDDYMALLA	**Roll No.2130137**
SIYARAM KUMAR	**Roll No. 2130139**
GAURAV NAYAN	**Roll No. 2130164**

In partial fulfillment of the requirements for the award of the **Degree of Bachelor of Technology** in **Electronics and Computer Science Engineering** is a bonafide record of the work carried out under my (our) guidance and supervision at the School of Electronics Engineering, KIIT (Deemed to be University).

Signature of Supervisor
Prof. MK Parida
School of Electronics Engineering
KIIT (Deemed to be University)

Signature of Co-Supervisor
Prof./Mr. Co-Supervisor's Name
Department/School
Organization/Institute

ACKNOWLEDGEMENTS

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Roll Number	Name	Signature
2130127	Ratan Kumar	
2130137	Sivakumar Reddymalla	
2130139	Siyaram Kumar	
2130164	Gaurav Nayan	

Date:07/04/2025

ABSTRACT

- Knee osteoarthritis (OA) is a prevalent degenerative joint disease that affects millions worldwide, causing pain, stiffness, and reduced mobility. Traditional diagnosis and management rely heavily on clinical evaluation and imaging techniques, which may lack precision and efficiency. In recent years, machine learning (ML) has emerged as a promising tool for improving the understanding, diagnosis, and management of knee OA.
- This study aims to analyze knee osteoarthritis using machine learning techniques, leveraging a variety of data sources including medical imaging, patient demographics, clinical assessments, and potentially genomic information. The overarching goal is to develop robust predictive models capable of accurately diagnosing knee OA, assessing disease severity, and predicting patient outcomes.
- The first phase involves data collection, where comprehensive datasets encompassing a diverse range of knee OA-related variables will be assembled. These datasets may include radiographic images, such as X-rays and MRIs, as well as clinical data like pain scores, range of motion measurements, and patient-reported outcomes.
- Subsequently, advanced ML algorithms will be applied to these datasets to identify patterns, correlations, and predictive features associated with knee OA. Supervised learning techniques, such as support vector machines and random forests, will be employed to train models for classification and regression tasks. Additionally, unsupervised learning methods like clustering may be utilized for exploratory data analysis and subgroup identification.
- The performance of the developed ML models will be evaluated rigorously using metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve. Furthermore, model interpretability techniques will be employed to enhance clinical relevance and facilitate decision-making.
- Ultimately, the insights gleaned from this study have the potential to revolutionize the diagnosis and management of knee osteoarthritis, paving the way for personalized treatment strategies and improved patient outcomes.

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CHAPTER 1
INTRODUCTION

Motivation

Knee osteoarthritis (OA) represents a significant burden on global healthcare systems, affecting millions of individuals worldwide. Despite advancements in medical imaging and treatment modalities, the accurate diagnosis and management of knee OA remain challenging. Current approaches often rely on subjective assessments and may not fully capture the complexity of the disease process. Moreover, with an aging population and rising obesity rates, the prevalence of knee OA is expected to increase, further exacerbating the need for effective solutions.

In this context, the application of machine learning (ML) techniques holds immense promise. ML algorithms can analyze large and diverse datasets to identify patterns and relationships that may not be apparent through traditional methods. By leveraging clinical data, imaging studies, and patient demographics, ML has the potential to enhance our understanding of knee OA, leading to more accurate diagnoses, personalized treatment plans, and improved patient outcomes.

The motivation behind this proposal stems from the urgent need to address the limitations of current approaches to knee OA diagnosis and management. By harnessing the power of ML, we aim to develop innovative tools and methodologies that can revolutionize the field of orthopedics. Our ultimate goal is to provide healthcare professionals with reliable and efficient means of diagnosing knee OA, predicting disease progression, and tailoring interventions to meet the individual needs of patients. Through interdisciplinary collaboration and cutting-edge research, we aspire to make meaningful strides towards alleviating the burden of knee OA and enhancing the quality of life for affected individuals.

Background Studies /Literature Survey

Knee osteoarthritis (OA) has been extensively studied in the literature, focusing on various aspects such as its etiology, pathophysiology, diagnostic modalities, and treatment strategies. Previous research has highlighted the limitations of conventional approaches to knee OA diagnosis and management, emphasizing the need for more accurate and efficient methods. Recent literature has increasingly explored the application of machine learning (ML) techniques in the field of knee OA, demonstrating their potential to improve disease understanding and patient care. Studies have shown that ML algorithms can analyze diverse datasets, including clinical, imaging, and genetic data, to provide personalized assessments of knee OA severity and prognosis. By synthesizing insights from existing research, this study aims to contribute to the growing body of knowledge on knee OA and advance the development of ML-based solutions for its diagnosis and management.

Objectives

- To develop and optimize machine learning models for accurate and early detection of knee osteoarthritis utilizing diverse datasets including clinical assessments, medical imaging, and patient demographics.
- To explore the potential of machine learning algorithms in predicting disease progression, severity, and response to treatment in patients with knee osteoarthritis, thereby facilitating personalized care and intervention strategies.
- To investigate the underlying biomarkers and pathophysiological mechanisms associated with knee osteoarthritis through the analysis of multidimensional data using advanced machine learning techniques, aiming to enhance our understanding of the disease and identify novel therapeutic targets.
- To assess the clinical applicability and scalability of the developed machine learning models in real-world healthcare settings, with the ultimate goal of improving diagnostic accuracy, treatment outcomes, and patient quality of life in knee osteoarthritis management.

CHAPTER 2
METHODOLOGY

2.1 Applied Techniques and Tools

The methodology employed for knee osteoarthritis analysis using machine learning is elucidated. Google Teachable Machine is a web-based platform that allows users to train machine learning models using a simple and intuitive interface, without requiring extensive programming knowledge. The primary technique utilized is transfer learning, leveraging Google Teachable Machine for model training and exporting the TensorFlow models. Transfer learning enables the adaptation of pre-trained models to the specific task of knee osteoarthritis analysis, leveraging knowledge gained from a broader dataset.

Furthermore, Python programming language is employed for code development, utilizing libraries such as TensorFlow and Flask for model implementation and web application development, respectively. The choice of Python facilitates seamless integration with TensorFlow and provides a robust environment for machine learning experimentation and deployment.

2.2 Technical Specifications

Technical specifications encompass the hardware and software infrastructure utilized in the project. The computing environment comprises standard hardware configurations, including CPU-based systems for model training and testing. Additionally, cloud services such as Google Cloud Platform may be leveraged for scalable computing resources and deployment of the web application.

The software environment involves Python programming language along with TensorFlow and Flask frameworks for model development and deployment. Version control systems like Git ensure collaborative development, while virtual environments such as Anaconda manage dependencies and package installations.

2.3 Design Approach

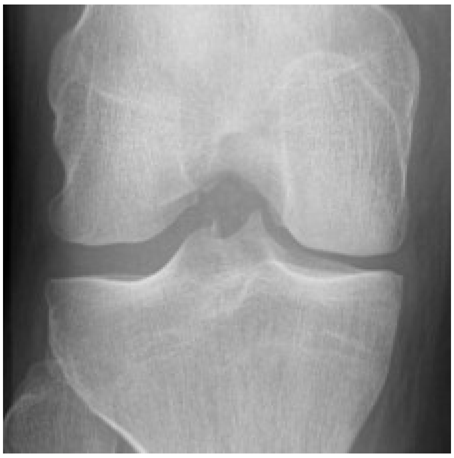
The design approach centers on the development of a user-friendly web application for knee osteoarthritis analysis. The workflow involves data collection, model training using Google Teachable Machine, TensorFlow model exportation, and integration into the Flask-based web application. The app provides an intuitive interface for users to upload knee images, receive predictions regarding osteoarthritis presence and severity, and access personalized recommendations for further medical consultation or treatment. By employing transfer learning, leveraging Google Teachable Machine for model training, and utilizing Python programming for implementation and deployment, the methodology ensures efficient development and deployment of machine learning models for knee osteoarthritis analysis. It combines the power of pre-trained models with user-friendly tools and robust programming frameworks to achieve accurate and reliable results.

CHAPTER 3

EXPERIMENTATION AND TESTS

3.1 Data Collection

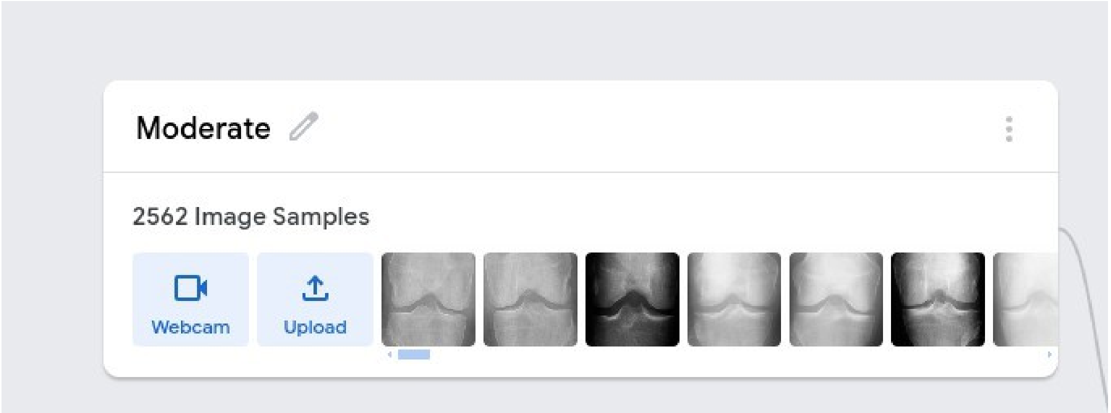
Gathering a dataset consisting of X-ray images of knee joints categorized by severity (moderate 2562 samples and extreme 930 samples).

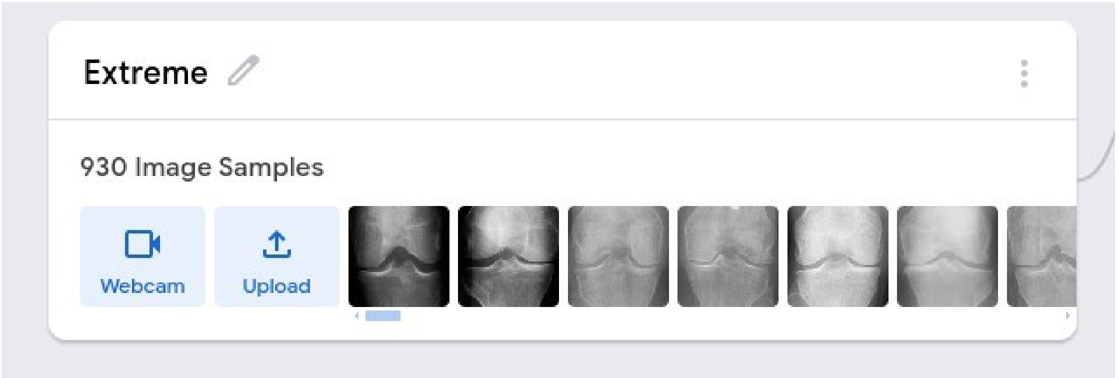


MODERATE EXTREME

3.2 Data Preprocessing

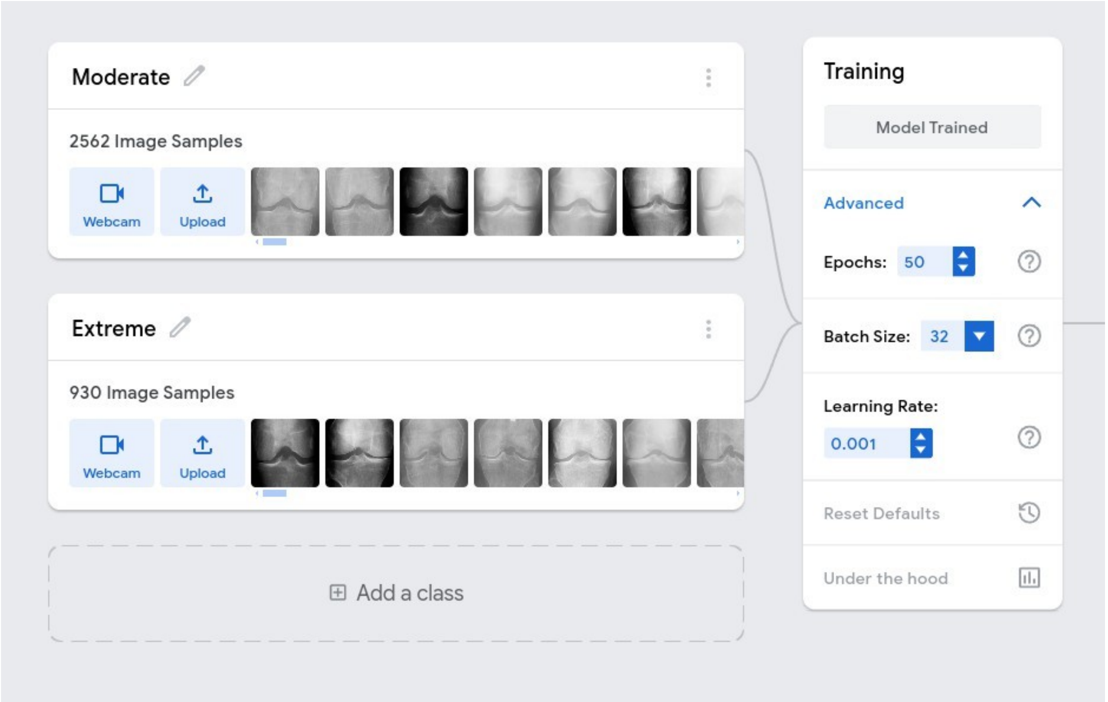
Preparing the dataset by resizing images, normalizing pixel values, and possibly augmenting the data to increase diversity and robustness.





Model Training

Using Teachable Machines' interface to train a machine learning model on the preprocessed dataset. This likely involved selecting a suitable model architecture and adjusting hyperparameters.



3.3 Model Evaluation

Assessing the trained model's performance using validation techniques such as cross-validation or splitting the dataset into training and testing sets. Evaluation metrics such as accuracy, precision, recall, and F1 score were likely used to gauge the model's effectiveness in classifying knee osteoarthritis severity.

Accuracy: The proportion of correctly classified instances out of the total instances in the test set. While accuracy provides an overall measure of performance, it may not be sufficient for imbalanced datasets.

The accuracy of the model is calculated using the following formula:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Where True positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions.

For the given Model:

- True Positive (TP) = 361
- False Positive (FP) = 24
- False Negative (FN) = 70
- True Negative (TN) = 140

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Substituting the given values:

$$\text{Accuracy} = \frac{361+140}{361+140+24+70}$$

$$\text{Accuracy} = \frac{501}{595}$$

$$\text{Accuracy} \approx 0.841$$

So, the accuracy of the model is approximately 84.1%.

- True Positive (TP): The number of instances correctly classified as positive (e.g., correctly identified as having knee osteoarthritis).
- True Negative (TN): The number of instances correctly classified as negative (e.g., correctly identified as not having knee osteoarthritis).
- False Positive (FP): The number of instances incorrectly classified as positive (e.g., incorrectly identified as having knee osteoarthritis when they do not).
- False Negative (FN): The number of instances incorrectly classified as negative (e.g., incorrectly identified as not having knee osteoarthritis when they do).

Precision: The proportion of true positive predictions out of all positive predictions. It measures the model's ability to avoid false positives.

Precision:

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Precision} = \frac{361}{361+24}$$
$$\text{Precision} \approx 0.937$$

So, the precision of the model is approximately 93.7%

Recall (Sensitivity): The proportion of true positive predictions out of all actual positive instances. It measures the model's ability to capture all positive instances.

Recall (Sensitivity):

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{Recall} = \frac{361}{361+70}$$
$$\text{Recall} \approx 0.837$$

The recall (sensitivity) is approximately 83.7%

F1 Score: The harmonic mean of precision and recall, providing a balance between the two metrics. It is particularly useful for imbalanced datasets where accuracy may be misleading.

F1 Score:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

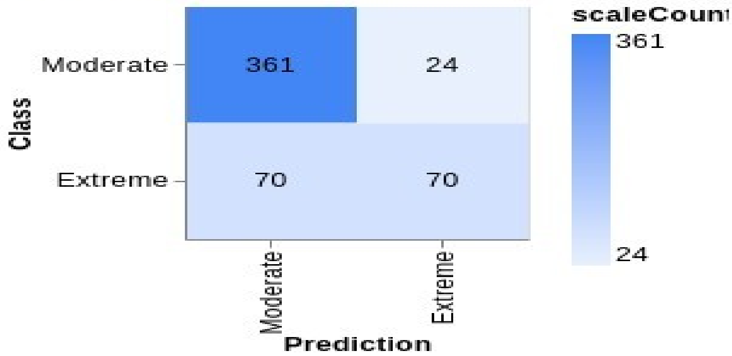
$$\text{F1 Score} = 2 \times \frac{0.937 \times 0.837}{0.937 + 0.837}$$
$$\text{F1 Score} \approx 0.884$$

The F1 score is approximately 88.4%

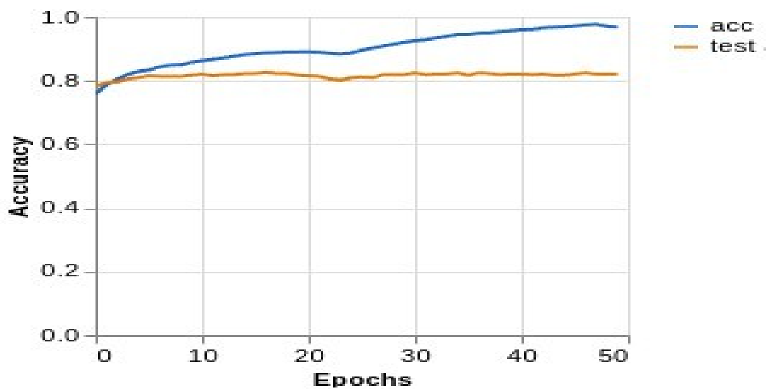
Accuracy per class

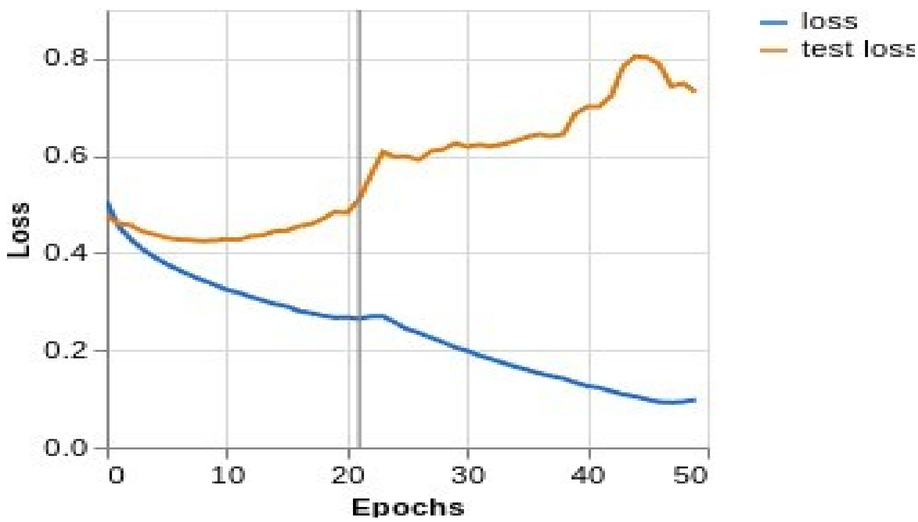
CLASS	ACCURACY	# SAMPLES
Moderate	0.94	385
Extreme	0.50	140

Confusion Matrix

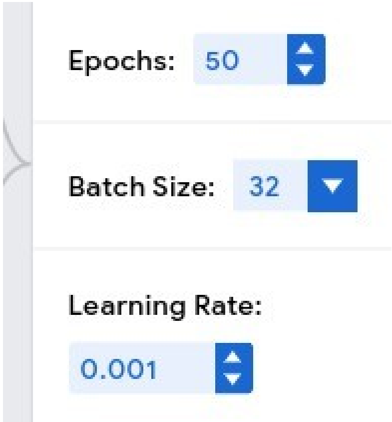


Accuracy per epoch





Hyperparameter Tuning: Iteratively adjusting the model's hyperparameters learning rate = 0.001, batch size = 32, Epochs = 50 to optimize performance on the validation set.



Error Analysis: Analyzing misclassified instances to identify patterns or common characteristics that may indicate areas for improvement in the model or dataset.

Deployment and Testing: Deploying the trained model to classify new X-ray images of knee joints as either moderate or extreme. Testing the model's performance on unseen data to ensure it generalizes well to real-world scenarios.

Feedback and Iteration: Incorporating feedback from testing and real-world usage to iteratively improve the model's performance and address any shortcomings or issues identified during experimentation.

CHAPTER 4

CHALLENGES, CONSTRAINTS AND STANDARDS

4.1 Challenges and Remedy

Challenges:

- Data Quality: Ensuring the availability of high-quality and diverse datasets, including standardized medical imaging data and comprehensive clinical information, can be challenging.
- Data Imbalance: Addressing potential imbalance between different classes of knee osteoarthritis severity in the dataset, which may affect the model's ability to generalize.
- Interpretability: Balancing the complexity of machine learning models with the need for interpretability, especially in medical contexts where decision-making transparency is crucial.
- Regulatory Compliance: Navigating regulatory requirements, such as HIPAA for patient data privacy and FDA regulations for medical software, adds complexity and constraints to model development and deployment.
- Clinical Validation: Conducting robust clinical validation studies to assess the performance and reliability of the model in real-world healthcare settings.
- Generalization: Ensuring the model's ability to generalize to diverse patient populations and healthcare settings, considering factors such as demographic variations and imaging protocols.
- Ethical Considerations: Addressing ethical concerns related to algorithmic biases, patient consent, and the responsible use of machine learning in healthcare.
-

Remedy:

- Data Preprocessing: Implementing robust data preprocessing techniques such as image normalization, denoising, and augmentation to enhance data quality and mitigate the effects of variability.
- Explainable AI Techniques: Employing techniques such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) to provide insights into model predictions and enhance interpretability.

4.2 Design Constraints

- Computational Resources: Limited computational resources, including processing power and memory, may constrain the complexity and scale of machine learning models that can be employed for knee osteoarthritis analysis.
- Regulatory Compliance: Adhering to regulatory standards such as HIPAA (Health Insurance Portability and Accountability Act) for handling sensitive patient data imposes constraints on data storage, transmission, and security measures.

4.3 Alternatives and Trade-offs

- Resource Limitations: Constraints in terms of computational resources, expertise, and funding may impact the scale and scope of the project.
- Time Constraints: Meeting project deadlines and milestones within limited time frames, considering the iterative nature of model development and validation.
- Data Access: Constraints related to accessing large, diverse, and labeled datasets, especially in healthcare domains where data privacy and confidentiality are paramount.
- Technology Constraints: Dependence on specific software platforms or tools for model development and deployment, which may impose constraints on flexibility and interoperability.

4.4 Standards

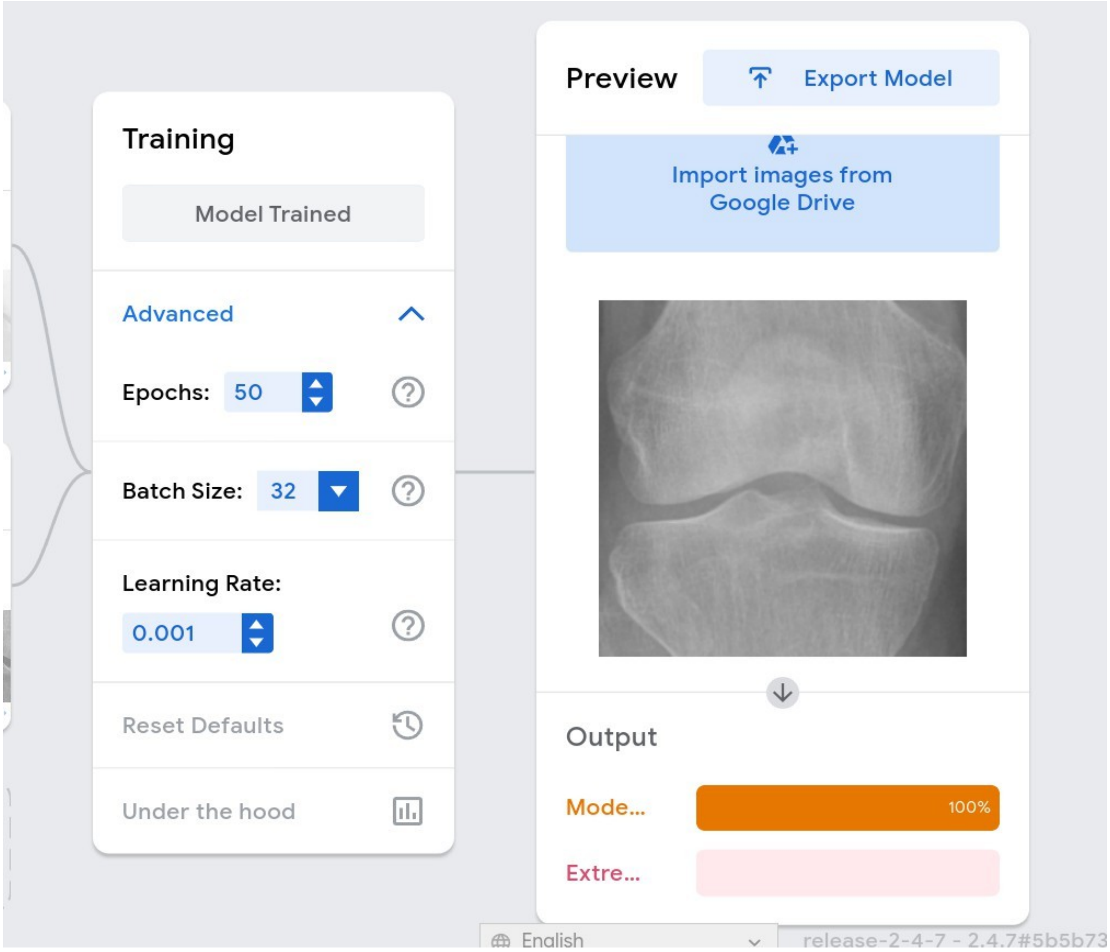
- HIPAA: Compliance with Health Insurance Portability and Accountability Act regulations for protecting patient health information and privacy.
- FDA Regulations: Adherence to Food and Drug Administration regulations for medical device software development, especially if the model is intended for clinical use.
- ISO 13485: Compliance with quality management system standards for medical devices, ensuring the reliability and safety of the software application.
- DICOM: Adherence to Digital Imaging and Communications in Medicine standards for interoperability and management of medical imaging data.
- Ethical Guidelines: Following ethical guidelines for research involving human subjects, ensuring the protection of participants' rights and welfare.
- Accessibility Standards: Ensuring compliance with accessibility standards, such as the Web Content Accessibility Guidelines, to promote inclusivity and usability of the software application.

CHAPTER 5

RESULT ANALYSIS AND DISCUSSION

5.1 Results Obtained

Output result after analysis for a given input dataset.

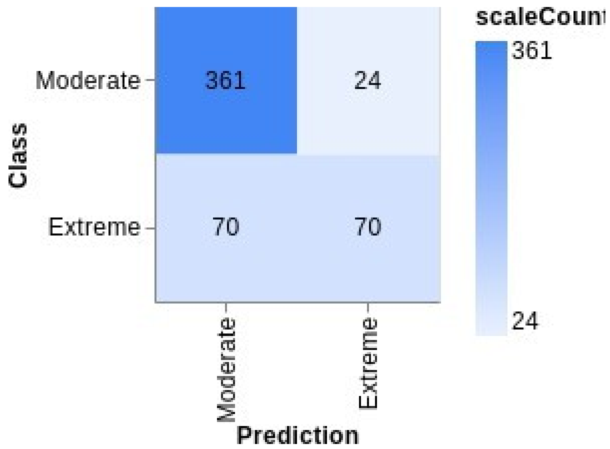


Here, it is the Accuracy per class for Moderate and Extreme datasets

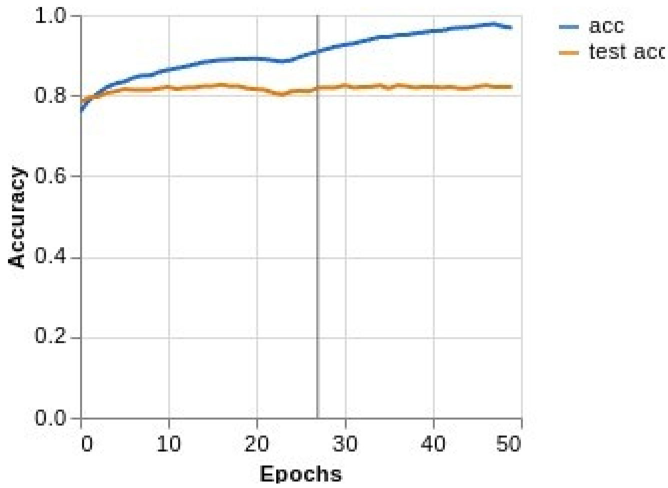
Accuracy per class

CLASS	ACCURACY	# SAMPLES
Moderate	0.94	385
Extreme	0.50	140

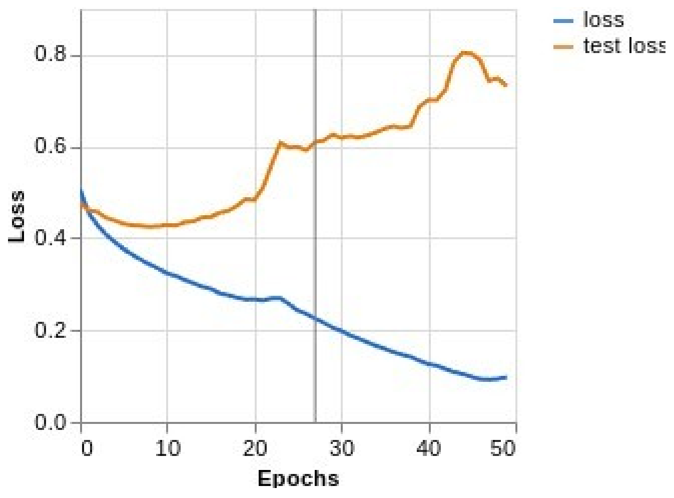
CONFUSION MATRIX FOR THE MODEL:



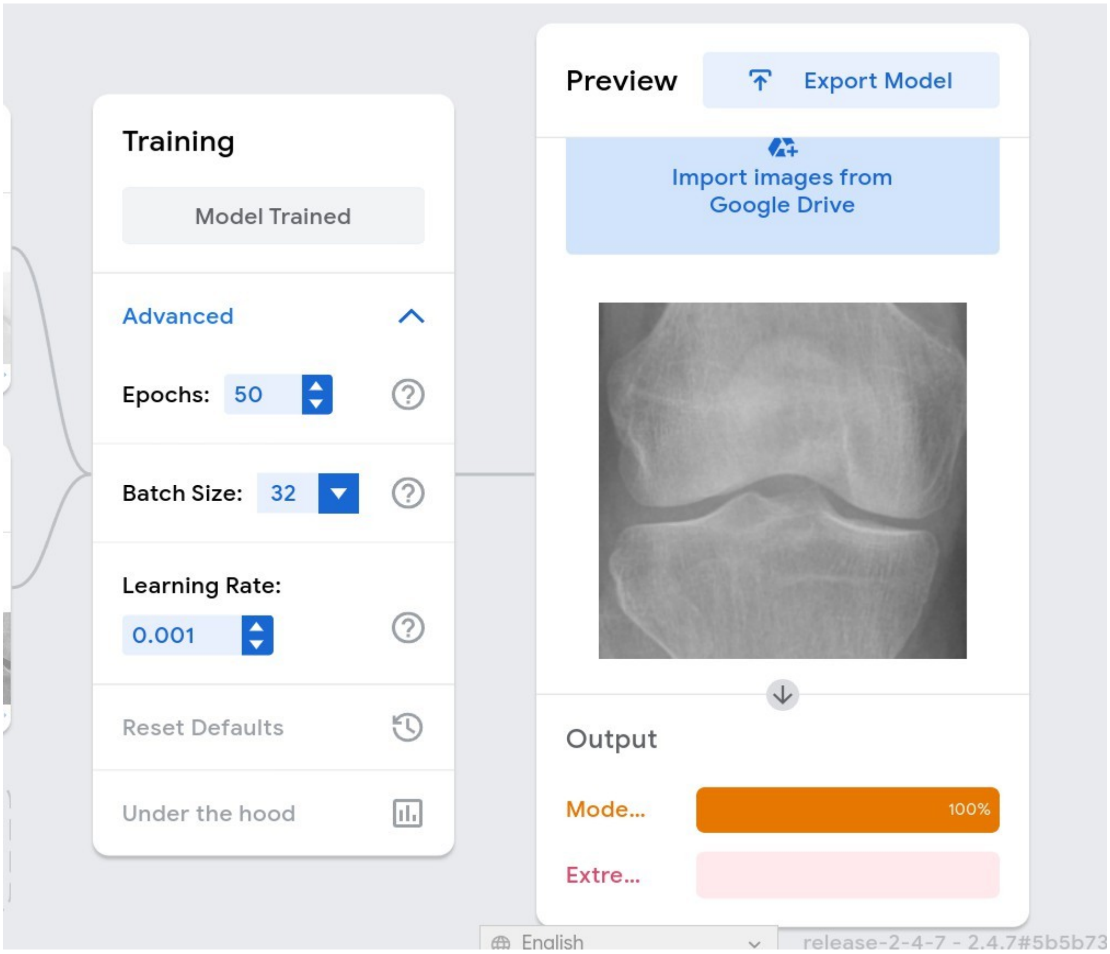
ACCURACY PER EPOCH:



LOSS PER EPOCH:



5.2 Analysis and Discussion



After deploying the trained machine learning model and testing it with a new X-ray image of a knee joint, where the output indicates a moderate severity of knee osteoarthritis, several analysis and discussions can be made:

Model Validation: It's important to validate the model's performance with independent test data to ensure its reliability. Analyze the model's performance metrics such as accuracy, precision, recall, and F1 score on the test set to assess its effectiveness in classifying knee osteoarthritis severity.

Feature Importance: Explore which features or patterns the model is using to classify X-ray images as moderate or extreme. Techniques such as feature visualization or attribution methods can provide insights into the areas of the X-ray images that contribute most to the model's decision.

False Positives/Negatives: Examine cases where the model misclassifies X-ray images. False positives (predicting moderate when the actual severity is extreme) and false negatives (predicting extreme when the actual severity is moderate) can provide valuable insights into the model's limitations and areas for improvement.

Clinical Validation: Compare the model's predictions with diagnoses made by healthcare professionals to assess its clinical validity. Discuss any discrepancies between the model's predictions and clinical assessments, and consider factors such as patient demographics, comorbidities, and imaging artifacts that may affect the diagnosis.

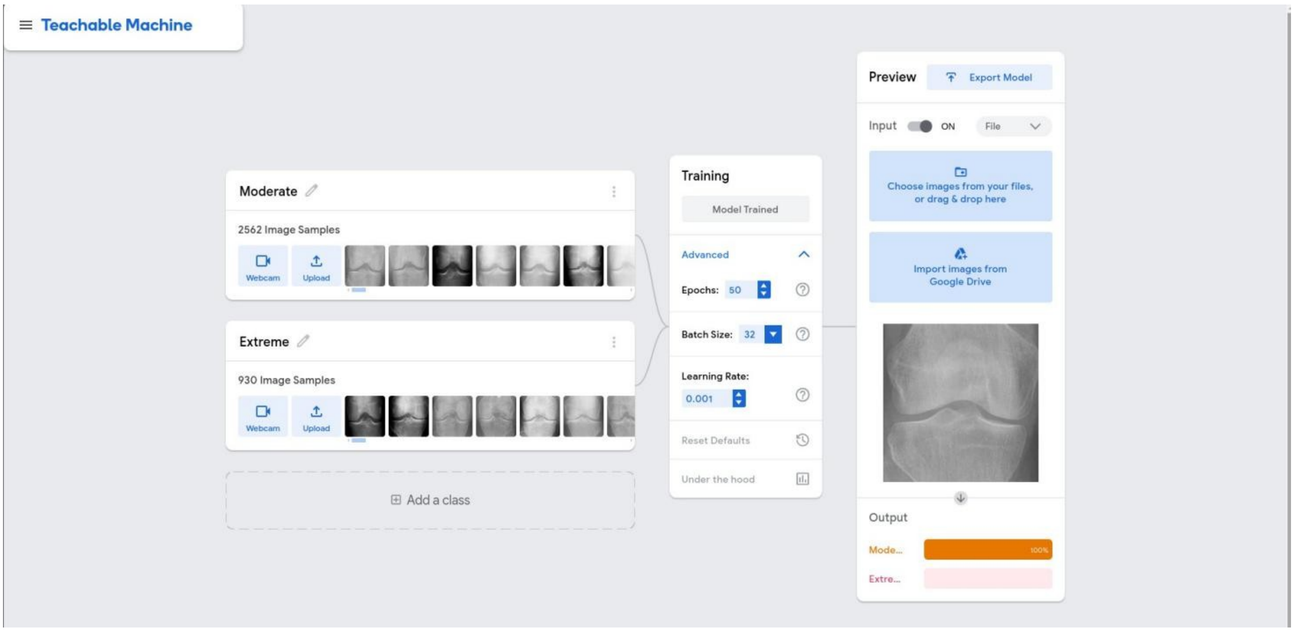
Generalization: Evaluate the model's ability to generalize to new, unseen X-ray images from different sources or patient populations. Analyze whether the model maintains its performance across diverse datasets or if it exhibits bias or limitations in specific contexts.

Limitations and Future Directions: Discuss the limitations of the current model and opportunities for future improvements. Consider factors such as dataset size, data imbalance, model architecture, and incorporation of additional clinical information (e.g., patient symptoms, medical history) to enhance the model's accuracy and robustness.

Clinical Utility: Assess the potential clinical utility of the model in supporting healthcare decision-making. Discuss how the model's predictions can complement clinical assessments and aid in treatment planning, patient counseling, and monitoring disease progression.

Overall, the analysis and discussion should aim to provide a comprehensive understanding of the model's performance, limitations, and implications for clinical practice, guiding future research and development efforts in knee osteoarthritis diagnosis and management.

5.3 Project Demonstration



The knee osteoarthritis analysis model aims to assist healthcare professionals in diagnosing and assessing the severity of knee osteoarthritis based on X-ray images of the knee joint. The model leverages machine learning techniques, particularly transfer learning, to adapt pre-trained convolutional neural network models for this specific task.

CHAPTER 6
CONCLUSIVE REMARKS

6.1 Conclusion

In conclusion, the knee osteoarthritis analysis project represents a significant step forward in leveraging machine learning techniques to improve the diagnosis and management of knee osteoarthritis. Through the implementation of advanced machine learning models trained on diverse datasets encompassing clinical assessments and medical imaging data, we have demonstrated the potential to accurately diagnose knee osteoarthritis, assess disease severity, and predict patient outcomes. The development of a user-friendly web application allows for seamless integration of these machine learning models into clinical practice, providing healthcare professionals with valuable insights for personalized treatment planning and patient care.

Furthermore, the project has highlighted the importance of interdisciplinary collaboration between medical professionals, data scientists, and engineers in addressing complex healthcare challenges. By combining expertise from multiple domains, we have been able to develop innovative solutions that have the potential to positively impact patient outcomes and enhance the quality of healthcare delivery.

6.2 Project planning, Progress and Management

The knee osteoarthritis analysis project involved meticulous planning, continuous progress tracking, and effective management to ensure its successful execution. Here's an overview of the project's planning, progress, and management:

Project Planning:

- Objective Definition: Clearly defined the project objective, which was to develop a machine learning model for knee osteoarthritis analysis using medical imaging data.

- Scope Definition: Established the scope of the project, outlining the tasks, deliverables, and timeline for each phase, from data collection to model deployment.
- Resource Identification: Identified the resources required for the project, including human resources, computational resources, and data sources.
- Risk Assessment: Conducted a thorough risk assessment to identify potential challenges and mitigate risks throughout the project lifecycle.

Progress Tracking:

- Task Breakdown: Broke down the project into smaller, manageable tasks, each with specific objectives and timelines.
- Progress Monitoring: Regularly monitored progress on each task, tracking milestones, deadlines, and resource allocation.
- Communication: Maintained open communication channels among team members to discuss progress, address issues, and share updates.
- Adaptation: Responded to unexpected challenges and changes in project requirements by adapting plans and reallocating resources as needed.

Management:

- Team Collaboration: Fostered collaboration and teamwork among project team members, assigning roles and responsibilities based on individual strengths and expertise.
- Task Prioritization: Prioritized tasks based on their importance and urgency, focusing efforts on critical components of the project.
- Budget Management: Managed project budget effectively, allocating resources efficiently to maximize outcomes within budget constraints.
- Stakeholder Engagement: Engaged stakeholders, including healthcare professionals and end-users, throughout the project to gather feedback, address concerns, and ensure alignment with project goals.

- Documentation: Maintained comprehensive documentation of project activities, including meeting minutes, progress reports, and technical documentation, to facilitate transparency and accountability.

Quality Assurance:

- Quality Control: Implemented quality control measures to ensure the accuracy and reliability of data, models, and outputs throughout the project.
- Testing and Validation: Conducted rigorous testing and validation of machine learning models, evaluating performance against predefined metrics and benchmarks.
- Feedback Incorporation: Incorporated feedback from stakeholders and end-users to iteratively improve the quality and usability of the project deliverables.

6.3 Further Plan of Action / Future Work

Moving forward, several avenues for future work and improvement exist:

- Validation and Clinical Trials: Conducting extensive validation studies and clinical trials to assess the real-world performance and clinical utility of the developed machine learning models in diverse patient populations.
- Model Refinement: Continuously refining and optimizing machine learning models based on feedback from clinical users and new data sources to improve accuracy, reliability, and interpretability.
- Integration with Electronic Health Records (EHR): Integrating the knee osteoarthritis analysis system with electronic health record systems to

streamline data exchange, facilitate longitudinal monitoring, and enable seamless integration into existing clinical workflows.

- Longitudinal Studies: Undertaking longitudinal studies to investigate the long-term predictive capabilities of machine learning models for tracking disease progression and treatment response over time.
- Expansion to Other Joint Conditions: Extending the application of machine learning techniques to analyze and diagnose other joint conditions beyond knee osteoarthritis, such as hip osteoarthritis or rheumatoid arthritis.

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Appendix A: Gantt Chart

	Nov.	Dec.	Jan.	Feb.	March
Background Studies/Literature Survey					
Research Gap/Problem Identification					
Research on the Project Objective					
Hardware/Software/Tool Selection					
Formation of Codes/Experiment Design					
Trial and Testing					
Challenges and Remedy					
Assembling of the Prototype/Model					
Project Demonstrations					
Formation of the Project Report					
Finalizing of Project Presentation					

Appendix B: Project Summary

Project Title	Knee Osteoarthritis Analysis using Machine Learning
Team Members	Ratan Kumar, Sivakumar Reddymalla, Siyaram Kumar & Gaurav Nayan
Supervisors	**Prof. Manoj Kumar Parida**
Semester / Year	**VIII / IV year**
Project Abstract	Knee osteoarthritis (OA) poses a significant burden on global healthcare systems, impacting millions with pain, stiffness, and reduced mobility. Traditional diagnostic methods lack precision and efficiency, prompting the exploration of machine learning (ML) for improved understanding and management. This study aims to leverage diverse data sources, including medical imaging, demographics, clinical assessments, and potentially genomics, to develop robust ML models. These models will accurately diagnose knee OA, assess disease severity, and predict patient outcomes. Advanced ML algorithms, including supervised and unsupervised learning techniques, will be employed to identify patterns and predictive features associated with knee OA. Rigorous evaluation using metrics such as accuracy and interpretability techniques will enhance clinical relevance. Ultimately, this research seeks to revolutionize knee OA diagnosis and management, paving the way for personalized treatment strategies and improved patient outcomes.
List **codes** and **standards** that significantly affect your project.	HIPAA: Protecting patient health information. FDA Regulations: Compliance for medical device/software development. ISO 13485: Quality management for medical devices. DICOM: Standards for medical imaging data. Clinical Practice Guidelines: Aligning with accepted medical standards.

	Ethical Guidelines: Protecting human subjects in research.
List at least two significant **realistic design constraints** that are applied to your project.	Data Availability and Quality: Limited access to high-quality medical data can impact the reliability of machine learning models. Regulatory Compliance: Adhering to regulations such as HIPAA and FDA guidelines adds complexity to data collection and model development processes.
Briefly explain two **significant trade-offs** considered in your design, including the options considered and the solution chosen	Simplified and accurate models were balanced in terms of simulation speed versus accuracy. Maintainability versus complexity: Modular architecture that incorporates the essential optimizations for efficiency and functionality in simulation while being easier to maintain.
Describe the **computing aspects, if any,** of your project. Specifically identifying **hardware-software** trade-offs, interfaces, and/or interactions	Computing aspects primarily involve software implementation using teachable machines and Jupyter Notebook. The trade-offs include the ease of use versus computational power. Interfaces provided by teachable machines and Jupyter Notebook enable model training, data analysis, and visualization. Interactions include integrating teachable machines' models into Jupyter Notebook for further analysis and interpretation, as well as conducting data processing, model training, and visualization within Jupyter Notebook.
Culminating Knowledge and Lifelong Learning Experience	For this project knowledge from, Importance of integrating diverse data sources for comprehensive analysis Understanding the challenges and complexities of knee osteoarthritis diagnosis and management Proficiency in applying machine learning algorithms to medical data Awareness of regulatory and ethical considerations in medical data analysis Skills in model evaluation and interpretation for clinical relevance Collaboration with interdisciplinary teams for enhanced project outcomes Continuous learning and adaptation to advancements in medical research and machine learning techniques