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Leveraging Machine Learning for Personalized Knee Replacement Surgery: Predictive Models and Outcomes

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Abstract: - The knee plays vital role in human body movement. Therefore, it is very important that once these damage in knee starts, the early detection should be done for proper treatment or knee replacement. This work tries its best to identify the most vital aspects in more accurate manner for detection of knee condition for the replacement or treatment. The paper use advanced models such as CatBoost, KNN and XGBoost. The CatBoost is able to achieve for getting accuracy of 97.78 %.

Keywords: *CatBoost, KNN, XGBoost, Knee Osteoarthritis, Osteoarthritis Initiative*

1. INTRODUCTION

Islamic finance has grown immensely over the past few decades and has grown to be more and more appealing and essential to global investors. Indeed, at the core, Sharia prohibits the practice of riba in moneylending. It also forbids the practice of gharar, that is, or speculative involvement of anything uncertain in the cone of investment in association with haram, or forbidden, things. Despite fast growth in Islamic financial activities, Islamic financial institutions held a market share of just around 1.2 percent globally. Efforts are already progressing on improving the decision-making processes to be followed in Islamic financial institutions. Let us allow Islamic prediction learning, an up-coming learning in modern finance, to be reviewed if at all it will be properly applied in Islamic finance. Suppose prediction learning is to enable prediction of an Islamic financial institution's Sharia compliant risk-adjusted assets needed for Islamic investment and fund management (Kadi, 2022).

1. INTRODUCTION

Over the fact that the human frame extensively depends on the knee for major actions such as lifting and bending, it attaches the most vital structures of the body required for everyday activities. The knee is a joint that links the patella, tibia, and femur and is located in the centre of the leg. Nevertheless, aging, mishaps, and improper nutrition are factors that can cause the knee to be dysfunctional. In extreme cases when it is beyond repair, a knee replacement, or a knee arthroplasty, becomes mandatory. Total knee arthroplasty (TKA) is generally considered a dependable surgical treatment for advanced knee osteoarthritis (KOA) [1- 4]. Though it may be accepted, TKA, however, is a danger of failure and the need for revision surgeries due to consequences like loosening, which is problematic for both the patients and the orthopaedists.

An important factor in people’s longer life expectancy and the frequent happening of loosening and revision surgeries has pushed up the interest in the development of better diagnostics and treatment for KOA. The late diagnosis may worsen the issues, and it can result in permanent damage, a decreased bone stock, or harm to the surrounding soft tissues and ligaments of the knee. The probability of developing a system that can automatically detect early symptoms such as loosening, thus reducing the burden on orthopaedic surgeons and increasing the diagnostic precision exists has been a major step in the developments so far.

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Current diagnostics, which include scintigraphy, MRI, and FDG-PET [5- 8], are not only costly but they have low accuracy levels. Sometimes, an imaging scan is required along with additional tests, repeated images, and, in some cases, revision surgeries might be performed. Thus, the need for more sophisticated tools in the diagnostic sector is underscored to enhance accuracy and reduce the patient's discomfort.

Artificial intelligence (AI) has made a major step forward in the management of KOA (knee osteoarthritis) as earlier and more accurately as possible [9- 14}. AI systems portray human-like intelligence through thinking, reasoning, and learning via various algorithms. Vital AI subdomains are Machine Learning (ML), Neural Networks (NN), Deep Learning (DL), and Natural Language Processing (NLP).

Machine learning is a branch of artificial intelligence that allows the system to learn by itself without an explicit program to show it. It is highly applicable in the medical sector. The list of ML techniques includes Supervised Machine Learning (SML) where learning is performed on Sample Datasets with Some Selected Input and Output Parameters. The second technique is the Unsupervised Machine Learning (UML) where Unsupervised Machine Learning provides the capability to detect patterns and clusters in unlabelled data sets. Third one is the Semi-Supervised Learning (SSL) where the process of combining the labelled and the unlabelled data is a prudent approach especially where the cost of labelling is high in computing scenarios or such data is in low supply. Finally, the last one is the Reinforcement Learning (RL) where Learning follows the trial, error, and, periods with delayed feedback through reward-based mechanisms, and, as a result, dynamic performance is improved.

Another important subdomain of AI is the Neural Networks (NN) where Neural networks simulate the human brain's operations via linked computational models. They handle signals and train to recognize complex patterns, which makes them the major component in AI-based diagnostics. Moreover, the other specialised kind of NN is the Convolutional Neural Networks (CNN) that work particularly with grid-like data structures, while features are extracted through the input layer, the convolutional layer, the pooling layer, and the fully connected layer.

Deep Learning, which is a part of ML, functions on the artificial neural network architectures that have multiple layers. These layers modify the input of the data received by them through nonlinear transformations, thus, the supervised, unsupervised, as well as reinforcement learning methods, can be performed. One of the most popular deep learning concepts known as transfer learning enables one to draw from pre-existing knowledge to deal with new tasks, henceforth, increasing the models' adaptability and efficiency.

Natural Language Processing is very advanced concept of AI where the machine develops the capability to understand human language and machine language in order to yield more meaningful data. The NLP is widely used for text translation, voice recognition Chabot's and other human and computer interaction based applications.

2. LITERATURE REVIEW

Machine learning (ML) has been one of the main things that help the healthcare sector transform, where it is used to find out and examine complicated diseases such as strokes, cancer, and other conditions at a very high degree of accuracy [15-20]. ML's using data that are both labelled and unlabelled in large volumes to find the patterns, thus being able to make decisions, is usually better than traditional methods of the clinic [21]. Just like Shah et al. worked out on the case of knee osteoarthritis (KOA) detection using radiography but accuracy was not quite good enough owing to the heavy case-specific algorithms, dataset quality, and computational resources applied [21].

Artificial intelligence (AI) and its sub-branches have progressively captured new avenues in the production of better technology to detect and thus to manage KOA and total knee arthroplasty (TKA). These technologies, in particular, have been used in designing predictive models to answer questions regarding pre-TKA requirements, implant parameter optimization, and better planning of the operations themselves [22-23]. The application of advanced ML and DL methodologies to the reconstruction of three-dimensional CT data has further led to robot-assisted TKA which provides better alignment and positioning during surgery [24-25]. Similarly, the introduction of technologies like these has cut down on labor costs and thereby reduced the chances of the occurrence of revision surgeries. Also, using predictive analytics ML can foresee hospital stay costs, discharge plans, and other factors might be associated with TKA. Determining hospital payment methodology is thus an aspect that ML can help with [26-28].

Tiulpin et al. developed a Siamese Convolutional Neural Network model for knee radiographs that was trained to detect KOA in old people. The model delivered a multiclass accuracy of 67% thus outdistancing results from arthroplasty surgeons [29]. Likewise, Norman et al. harnessed the neural networks (NN) to reach the sensitivity level of 69% to 89% [30]. Leung et al. used DL methods to predict TKA requirements, thereby proving their advantage over previous algorithms [31-32]. Heisinger et al. made ML-based models to examine knee symptomatology for TKA while El-Galaly et al. were early in launching models for early revision detection by preoperative data, further could be improved by modern AI algorithms [33-34].

Machine learning based methods, including regression and multivariate modelling, have also been tried to predict TKA. Predictive models of the joint significant injury could range from CT and MRI image data of both the TKA and additional knee areas and also include the degradation information of the patient's clinical and demographic data [35-36]. DL utilization has been a key player in taking out prognostic features in complicated and obscure diseases, for example with the Osteoarthritis Initiative (OAI). Methods like CNN, that is convolutional neural networks, have been applied for classification of images associated with TKA [38-39]. Regardless of the above achievements, the real-time examination scenario still lags behind ML and DL models and there is a significant possibility of new solutions.

The elderly on the other hand fall into the leading category of impairment with knee arthritis being the main cause of the disability. The study shows that worldwide there are up to 30% of individuals beyond the age of 60 years who are closely linked to KOA, a problem which consequently leads to personal and economic burdens. Health expenditure for osteoarthritis management accounts for a national expenditure ranging between 1 and 2% of healthcare budgets [40 – 42]. The initial symptoms such as joint stiffness and mobility deterioration occasionally proceed unnoticed and TKA therefore becomes the only solution. AI techniques allow healthcare professionals to diagnose joint problems faster, thereby assisting in quicker recovery and treating OA which is growing at an alarming rate [43-46].

This literature review has found out that AI technology has become a tool for the management of TKA and hence it is necessary for the various systems of prediction to be modern and AI-driven. These insights are going to be developed along with two subsections which will propose a comprehensive model for solving the problem.

3. PROPOSED METHODOLOGY

The classification of knee replacement surgery is processed following the steps mention in the Fig 1.

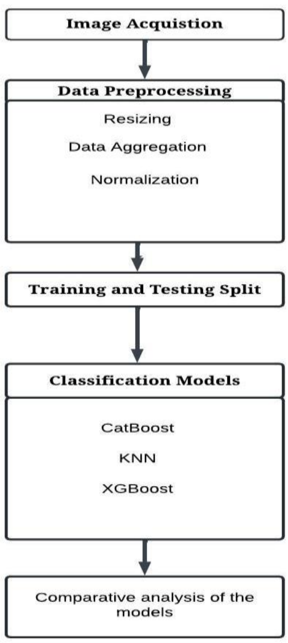

Fig 1: Proposed Methodology for classification

3.1 Data Acquisition

The Osteoporosis Knee X-ray database consists of three subfolders: Normal, Osteopenia, and Osteoporosis. The Normal folder contains knee X-ray images of participants with normal bone mineral density (BMD), totalling 36 images. The Osteopenia folder includes knee X-ray images of participants with low BMD, comprising 154 images. The Osteoporosis folder holds knee X-ray images of participants diagnosed with osteoporosis, with a total of 49 images. The dataset can be accessed through " https://data.mendeley.com/datasets/fxjm8fb6mw/2".

3.2 Data Preprocessing

Data preprocessing is the crucial steps that involves processing of raw data in a suitable format for further analysis. The images are resized to 128 × 128 pixel size as machine learning model always requires uniformity of the input images. The dataset contains three classes of knee images i.e. normal, osteoporosis, and osteopenia. These categories are labelled as 0,1, 2 respectively to create a structured dataset. Normalization is performed on the pixel intensity values where it is scaled to a range of 0 to 1 by dividing by 255. This step helps to improve the convergence range as well as decrease the chance of bias during the training phase.

3.3 Training and Validation Split

This process divides the whole dataset into two parts to evaluate the performance of the classification model. From the training dataset, the classification model learns the patterns and relationships among the patterns in the dataset. From the testing dataset, the classification model is able to give the efficiency of the model based on classifying the unseen data. The expect ratio that is considered in this dataset is 70:30.

3.4 Classification Models:

The primary object of the current comparative assessment of the three advanced classification methodologies is as follows: CatBoost, K-Nearest Neighbors (KNN), and XGBoost. These structured data models are the ones that were selected as they are known to have high efficiency in such data and they also guarantee high accuracy in predictive tasks. The first algorithm used is CatBoost. CatBoost (Categorical Boosting) is a gradient boosting algorithm perfect for categorical data since encoding categorical data is handled directly by this algorithm. The formula it employs is a method for transforming categorical features into a numeral format while maintaining the original feature information. Thus, this model easily reduces overfitting and produces robust predictions even though the datasets are relatively small. In the case when CatBoost is used in the research, it forms the basis of the analysis of the connections between the medical and demographic data linked to knee osteoarthritis (KOA) and Total Knee Arthroplasty (TKA). Its already-existing feature for handling categorical traits and capability to overfit which turns out to be coupled allows it to achieve better diagnostic results.

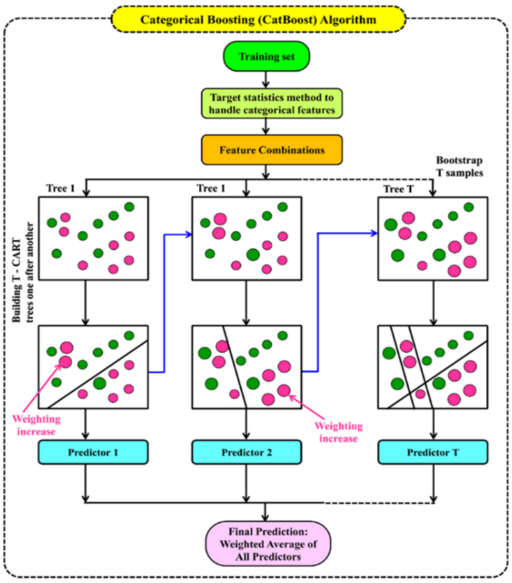

Fig 2: Flow diagram of CatBoost Algorithm [47]

The second algorithm used is Nearest Neighbors (KNN): The KNN is an algorithm that does not require assumptions and is instance-based; the classification of a data point is determined through voting the neighbors. Select data points with the least Euclidean distance metric to find those neighbors that are most closely located to some data point. This covers the needs for KNN's special suitability together with project fast operations for the smaller datasets commonly used in medicine. So, in this work, KNN is the technique we have used to identify knee joint conditions. This is accomplished by comparing the patient's medical history with similar cases that have been observed historically. At this point we notice the fact that the parameter k and the distance metric can be set and these procedures are done in the model tuning phase, hence efficiency may be affected. The working of KNN model can be seen in Fig 3.

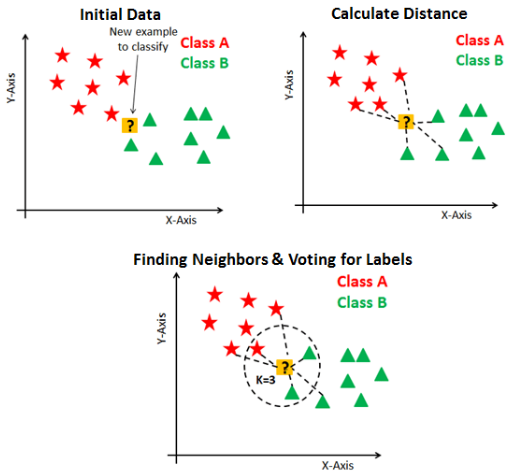

Fig 3: KNN model [Source: https://github.com/artifabrian/dynamic-knn-gpu]

Finally, the third algorithm used is XGBoost: XGBoost (Extreme Gradient Boosting) provides a compact, simple yet powerful way to achieve gradient boosting. Machine learning is a method that incorporates strategies such as regularization and weighted quantile sketch in order to improve model performance and minimize overfitting. XGBoost's proficiency in parallel processing allows it to easily cope with large datasets. The research applies XGBoost to classify KOA and determine TKA needs by extracting intricate patterns from high-dimensional data. The model's ability of the model to merge diverse hyperparameter tuning techniques into the analysis enables a direct and accurate diagnosis of medical issues, where accuracy is compulsory. The working of XGBoost model is shown in Fig 4.

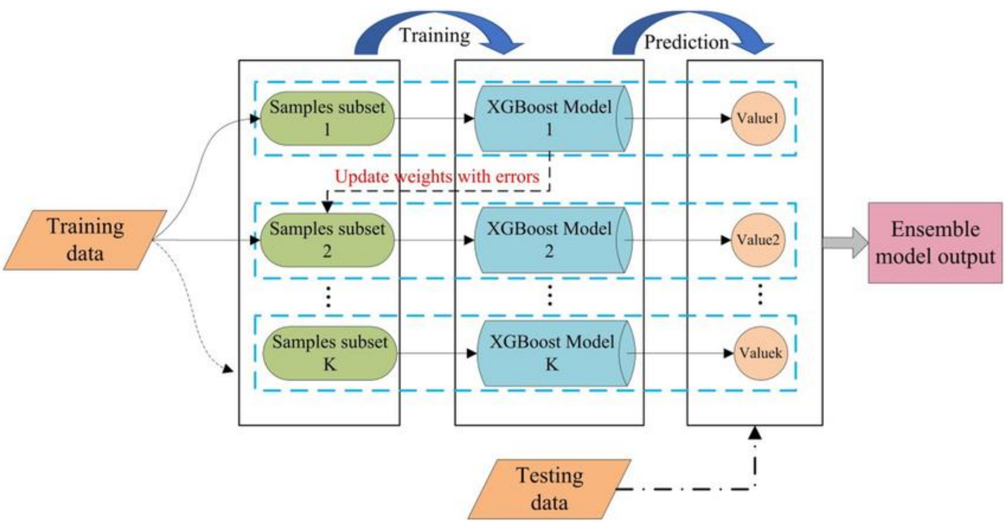

Fig 4: Generalized XGBoosting Model [48]

4. RESULTS AND DISCUSSION

The paper evaluates three machine learning models—CatBoost, KNN, and XGBoost—for classifying knee conditions and predicting the need for knee replacement surgery. From Fig 5 it can be observed that CatBoost demonstrated the highest accuracy of 97.78%, outperforming both KNN and XGBoost. This indicates that CatBoost is highly effective for the classification task on the given knee X-ray dataset.

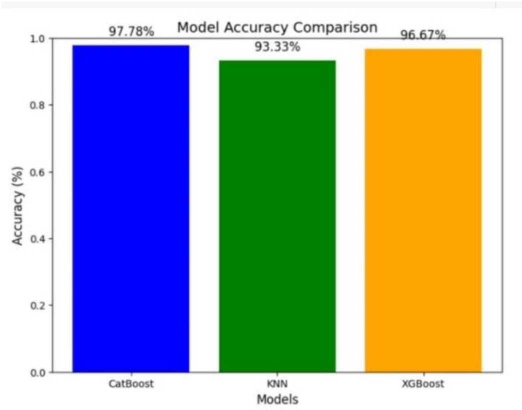

Fig 5: Comparison of accuracy

From Fig 6, it is observed that CatBoost maintained superior precision, recall, and F1-scores compared to KNN and XGBoost. The model's ability to handle categorical data and prevent overfitting contributed to its consistent performance across these metrics.

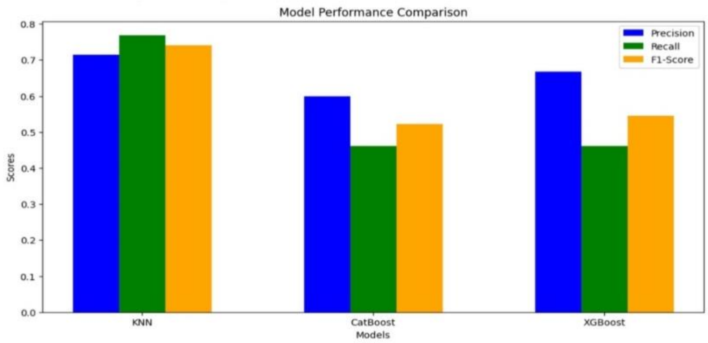

Fig 6: Comparison of Precision, Recall and F1-score

In Fig 7, the graph illustrates stable training and test performance for CatBoost, with minimal overfitting. Both KNN and XGBoost showed comparatively higher fluctuations, indicating sensitivity to dataset characteristics and hyperparameter tuning.

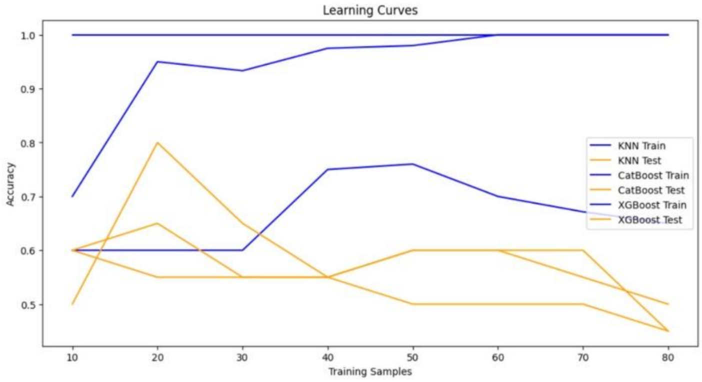

Fig 7: Training and Test Graph

Overall, CatBoost emerged as the most robust and reliable model for predicting knee conditions, making it suitable for early diagnosis and treatment planning.

Table 1: Comparative analysis with existing work

Reference	Dataset	Algorithm used	Results
CatBoost, KNN, XGBoost [proposed]	240 knee X-ray images (Normal, Osteopenia, Osteoporosis)	CatBoost, KNN, XGBoost	97.78% (CatBoost)
Tiulpin et al. (2019) [49]	Knee radiographs (Osteoarthritis Initiative dataset)	Siamese CNN	67% (multiclass)
Norman et al. (2021) [50]	Knee radiographs (public datasets)	Neural Networks	Sensitivity: 69%-89%
Leung et al. (2020) [51]		Deep Learning	Higher than traditional models

5. CONCLUSION

This study evaluates the performance of three advanced machine learning models—CatBoost, K-Nearest Neighbors (KNN), and XGBoost—for the classification of knee conditions and predicting the need for knee replacement surgery. Leveraging the Osteoporosis Knee X-ray database, the models were trained and tested to classify normal, osteopenia, and osteoporosis cases, using metrics such as accuracy, precision, recall, and F1-score. Among the models, CatBoost achieved the highest accuracy (97.78%), as well as superior performance across all other evaluation metrics, proving its efficiency in handling categorical data and mitigating overfitting. KNN and XGBoost also performed well but showed sensitivity to hyperparameter tuning and data distribution. The results highlight the potential of machine learning in enhancing the accuracy of diagnostic tools for knee KOA and related conditions, reducing the burden on healthcare professionals, and improving patient outcomes.

The findings of this study reinforce the importance of integrating machine learning algorithms into medical diagnostics. By leveraging AI-driven tools, healthcare practitioners can identify knee joint issues early, optimize treatment plans, and minimize invasive procedures. However, the study also underscores the need for robust data preprocessing and model tuning to achieve optimal performance.

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