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Knee Osteoarthritis Classification: A Hybrid Approach with Machine Learning Classification

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ABSTRACT

Osteoarthritis (OA) is characterized by the degradation of the layer between the joints. Osteoarthritis (OA) is a situation that results from deformation of the layer between two bones. Pain where the bone joins Osteoarthritis affects all patients. It mostly harms the cartilage in the joints, which fallouts in stiffness, discomfort, and edema. It is the main cause of soreness and debility. It is anticipated that as the people ages and obesity rates rise, the occurrence of OA would gradually rise as well[1]. Pain while activity or movement in elderly people individuals can notably disrupts their daily activities, reducing ability to function alone. Common causes may due to arthritis, muscle weakness, and joint degeneration. Managing pain through proper medical treatment can restore their daily comfort for osteoarthritis patients

One of the main musculoskeletal conditions that contribute to years of incapacity is osteoarthritis. Since osteoarthritis is more dominant in older adults (nearly 70% of those over 55), its frequency is predictable to rise as the world's population ages. Athletes and those who have experienced joint stress or injury may be at risk for osteoarthritis, even though it typically first manifests in the late 40s to mid-50s. About 60% of people with osteoarthritis are women [5].

Classification shows an essential part in diagnosing joint degeneration by measuring the severity using algorithms designed for machine learning. This helps to design optimal treatment plans. Proper diagnosis improves mobility and quality of life. So, classification is plays important part in diagnosing Osteoarthritis in patients. Numerous machine learning methods are available for the analysis and ordering of osteoarthritis. Multiple machine learning techniques gives different results. In this article combinational machine learning techniques are applied. Combined study may be beneficial for getting more accurate results in medical applications working on Osteoarthritis detection. This paper represents a combination of machine learning based approach for binary classification. Features are mined using Histogram of Oriented Gradients and Gray Level Co-occurrence Matrix is united together in the CSV format, which was then passed as input for machine learning classification models. Results demonstrate advantageous outcomes with high accuracy and significant potential for medical application.

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1. INTRODUCTION

The largest synovial joint within the human body, the patella, ligaments, distal femur, proximal tibia and cartilage make up the knee [1]. The synovium produces synovial fluid, which lubricates and nurtures the vascular cartilage. Due to its high pressure and frequent use, this joint is often the location of painful diseases, such as osteoarthritis. The process of OA assessment is usually sluggish and can take years. Additionally, the complaint may develop in stages or exhibit gradual modifications over time, which could lessen its severity and indicators.

Osteoarthritis (OA) is a prolonged stiffness caused due to the loss of cartilage tissue and damage in the supporting bone, joint pain and movement restrictions. Traditional diagnostic methods, such as radiological scans and Medical evaluations, commonly lead to a late-stage detection of osteoarthritis. These methods mostly investigate joint damage once it has reached an advanced stage Medical imaging, even though effective in finding Joint tissue breakdown, may not reveal preliminary Molecular and cellular changes in the joint. Clinical studies depend upon patient's symptoms and physical examinations, can be opinion based and may vary based on pain sensitivity in individual and the physician's proficiency. As a result, by the time osteoarthritis is diagnosed, the condition may have advanced significantly, making treatment less effective and substantially compromise the patient's lifestyle.

9.9 million office-based doctor visits with osteoarthritis as the primary diagnosis[2] .

Over 30 million people in the US and over 10 million in Asia, Middle East, Europe and South America the suffer with this most common type of arthritis[3]. Numerous biological, pharmacological, and environmental risk factors are believed to contribute to the onset and development of this complaint, despite the fact that there is now no known remedy.

Figures 1 and 2 below showed a sample of typical and affected by knee osteoarthritis x-ray images.

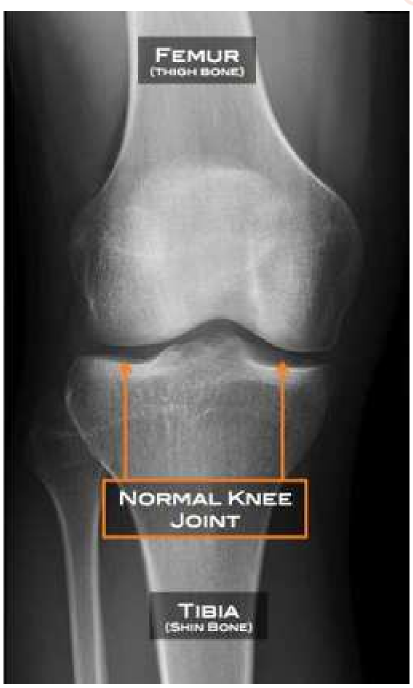


Figure 1: Image of a Normal Knee [20]

Figure 2: Image of Osteoarthritis in the Knee [20]

Machine learning (ML) introduced a new approach has the ability to significantly reshape treatment strategies and capability of OA classification, facilitating earlier medical response and positive patient prognosis. This study investigates the capability of different ML algorithms in classifying Knee osteoarthritis. By applying automated techniques, the goal is to classify actual approaches for Osteoarthritis detection and find out appropriate solution for practical medical applications. This paper explores the use of two methods for extracting features from images namely Histogram of Oriented Gradients and Gray Level Co-occurrence Matrix. Gray Level Co-occurrence Matrix is used to detention structural details that aid in OA classification while HOG focuses on edge detection. These extracted features are then combined together to form a wide dataset, which permits for a more inclusive and steady assessment of the health of the knee joint. Numerous classification techniques, including SVM, K-Nearest Neighbor, Decision Tree, Random Forest, Logistic Regression, Naive Bayes.

Literature Review

Millions of people have osteoarthritis in their knees as a result of joint disease, which lowers a patient's quality of life. It is becoming more widespread throughout the world and is one of the primary causes of debility in the elderly. The medical sciences always benefit from the use of advanced techniques because they can identify and treat patients with knee osteoarthritis in a short amount of time, giving them early relief. In recent decades, research on machine learning techniques has demonstrated the ability to automatically diagnose and classify knee osteoarthritis by extracting useful information from patient-reported outcomes, clinical data, and medical imaging. Knee osteoarthritis classification can be made extra precise and flexible with the application of machine learning, feature selection, and other image processing and ensemble learning techniques.

Amit Gupta et al. [3] worked on the machine learning techniques that predictions the danger in knee osteoarthritis. For the purpose of predicting knee osteoarthritis, Convolutional Neural Network and Long Short-Term Memory techniques were merged. However, with only minor changes in the CNN-based methodology, the model's accuracy rose sharply to from 74 % to 96%. This improved performance shows how these machine learning models can be used to rapidly classify people who are meaningfully more likely to develop knee osteoarthritis, thereby opening up chances for preventative care. These findings emphasize how important machine learning could be for osteoarthritis early detection, treatment and offering doctors and other healthcare professionals a useful tool to reduce the prevalence and severity of the condition.

This study presents a novel methodology to early discovery of osteoarthritis in the knee[4]. Training and testing are conducted using images from Mendeley Dataset VI. In addition to CNN with LBP and CNN with HOG, the projected model also uses joint space width to extract the region of interest's features. The KL system and multiclass classifiers such as SVM, RF, and KNN are used to categorize knee osteoarthritis. The pictures go through five-fold confirmation in addition to cross-validation. According to cross-confirmation, the proposed method has a 97.14% accuracy rate.

The texture characteristics of the patellar region were investigated by Bayramoglu et al. [5] using lateral view X-rays. Clinical variables, deep convolutional neural network structures, and handcrafted features were all compared and studied. The study proposed a stacked model that practices a second-level machine learning model to combine clinical features and patellar texture predictions. According to the findings, knees with and without patellofemoral osteoarthritis have different patellar bone texture characteristics. As a result, patellar bone texture traits may one day serve as novel imaging biomarkers for osteoarthritis diagnosis.

In order to address the issue of elderly individuals with osteoarthritis in their knees, the author of [6]tried to develop an application utilizing the six pre-trained prototypes namely MobileNetV2, DenseNet121, ResNet101,VGG19,VGG16 and InceptionResNetV2. The binary classification and the severity classification for osteoarthritis in the knee were the two classification types that were subsequently used. According to the revisions, using the specified datasets, Dataset III, Dataset II, and Dataset I, the ResNet101 model accomplished maximum classification accuracies of 69%, 83%, and 89%, respectively.

The authors [7] developed a tool to recognize and classify knee osteoarthritis from digital X-ray images using the Kellgren-Lawrence classification system. Additionally, they demonstrate how knee osteoarthritis can be assessed using deep learning techniques. The authors established a tool for identifying and classifying knee osteoarthritis from X-ray pictures using the Kellgren-Lawrence grading system. The authors also utilized additional pre-trained method, AlexNet by transfer learning, to classify the severity of osteoarthritis. Furthermore, the region proposal network was trained using the manual mining of the knee part as the ground truth image, and the knee joint X-ray images were organized by health specialists using the Kellgren-Lawrence score.

Article [8] suggested a rapid and active technique for classifying X-ray images using Gray Level Co-occurrence Matrix and Local Binary Patterns in order to boost image classification correctness and decrease testing and training time. After eliminating the GLCM and LBP from the converted image, the radiographs were divided into two patient groups based on these features: One hundred healthy individuals and one hundred pathological cases of osteoarthritis. The classification was authorized using the cross-validation method. The GLCM had correctness 77%, whereas the LBP methodology had correctness 82.5%. Furthermore, the mixture of the two techniques, LBP and GLCM, amplified the prediction accurateness consuming the LogitBoost techniques by 91.16%.

S. M. Ahmed et al. [9] propose a model including two separate components. The first model, which has five classes, employs support vector machines for classification, principal component analysis to reduce dimensionality and suggested pre-trained CNN for feature mining. Even though the second framework slightly changed the steps of the first framework, the pre-trained CNN that was initially intended for the first agenda was changed to suitable for two classes, after that three classes, and finally four classes-based models using the TL idea.

According to experimental results, performance increased when fewer multiclass labels were used; binary class tags overtook all others, achieving a 90.8% exactness rate.

The authors [10] used the Active Contour Segmentation technique to section a proportion of the X-ray image to identify the condition. A number of features, including Haralick, First Four Moments, Statistical, Shape and Texture are considered and categorized applying the Random Forest classifier. The planned approach produces 87.92% classification exactness.

Two sets of knee X-ray datasets descriptions were used by the author in this paper [11]. In this study, machine learning algorithms were employed to carry out feature extraction approaches for classification. GLCM and other texture feature vectors are produced through feature extraction. According to the dataset, the proposed model uses random forest to reach a maximum accuracy of 84.47%.

TABLE I. Summary of literature Review.

Ref. No	Dataset	Data	Pre-Processing	Feature Extraction/Classification	Results
[3]	Mendeley Dataset VI	Knee X-ray images	Minor CNN-based adjustments	CNN + LSTM for prediction	Accuracy increased from 74% to 96%
[4]	Osteoarthritis Initiative	Knee X-ray images	Cross-validation, five-fold validation	LBP, HOG, CNN for feature extraction, multi-class classifiers (SVM, RF, KNN)	Accuracy of 97.14%
[5]	Patellar X-ray Images	Lateral view X-ray images	Texture analysis	CNN features + hand-crafted features, stacked model	Classification of patellofemoral OA based on texture features
[6]	Dataset I, II, III	Knee X-ray images	Pre-trained models (VGG16, VGG19, etc.)	ResNet101 for classification	Max accuracy: 69%, 83%, 89% for datasets I, II, III
[7]	X-ray images	Knee X-ray images	Region proposal network (RPN)	AlexNet + transfer learning, medical expert grading	Predicts knee OA severity based on Kellgren-Lawrence score
[8]	Osteoarthritis Initiative	Knee X-ray images	GLCM, LBP	LBP, GLCM + LogitBoost	LBP accuracy: 82.5%, GLCM accuracy: 77%, combined: 91.16%
[9]	Knee X-ray images	Knee X-ray images	Feature extraction with CNN	SVM, PCA for classification	Binary class accuracy: 90.8%
[10]	Knee X-ray images	Knee X-ray images	Active Contour Segmentation	Random Forest classifier with feature sets (Haralick, etc.)	Accuracy: 87.92%
[11]	Knee X-ray images	Knee X-ray images	Feature extraction (GLCM)	Random Forest classifier	Accuracy: 84.47%

Proposed Methodology

Proposed system suggested machine learning-based image classification in this study for medical X-ray pictures. Preprocessing the X-ray pictures is the first stage of the suggested method. This enhances image quality and makes analysis easier, particularly for automated diagnosis of disorders like osteoarthritis. In order to analyze bone structures and potentially detect osteoarthritis, X-ray images were then submitted to feature extraction. To examine the texture and structure of medical pictures, hybrid extracted features are created by joining features from the Histogram of Oriented Gradients feature mining technique and the Gray-Level Co-occurrence Matrix feature mining technique .In the subsequent stage, these extracted features are fed into classifiers that identify osteoarthritis, such K- Nearest Neighbor, SVM, Logistic Regression, Random Forest, Decision Tree, Naive Bayes.

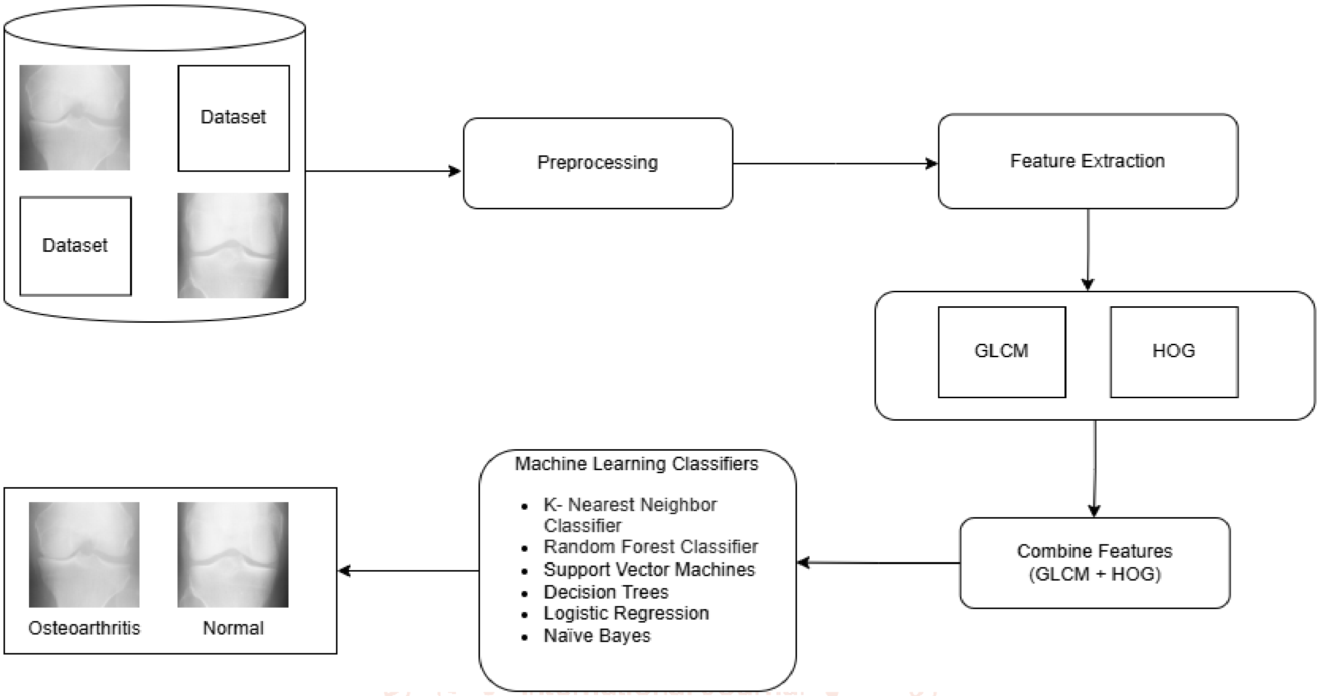


Figure 1: Proposed system

Fig. 1 displays the procedure for the suggested strategy. Data acquisition, dataset preprocessing, feature mining, and ordering are the four primary stages of the methodology. First, the Osteoarthritis Initiative provided the data for X-ray pictures of knee osteoarthritis, which is available on Kaggle. This dataset is separated into three

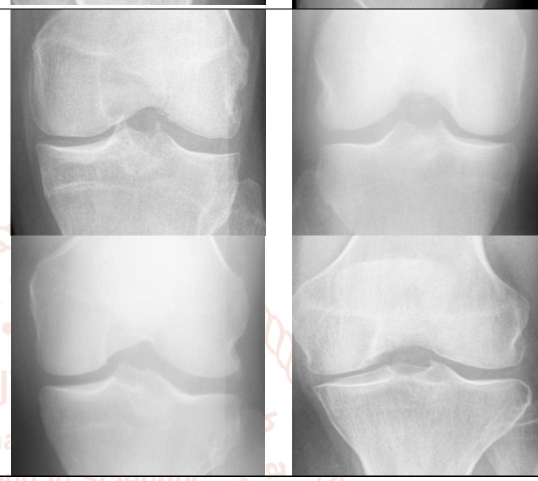
distinct image sets (train, test, and valid), each of which has two folders. One is for knee x-ray pictures that are normal (normal) and the other are for osteoarthritis-positive (osteoarthritis) x-ray images.

Regarding clarity and location, the knee joint X-ray image dataset is unsuitable for use as an input. Consequently, data preparation is necessary, wherein the images are altered to accurately depict the joint region where the knee osteoarthritis information is most likely to be found. Because the dataset varies in size, the image is shrunk to 224x224 during the preprocessing step. This preprocessed images separated into three datasets namely, testing set, training set, and validation set. Each of this datasets was separated into two classes namely osteoarthritis positive and osteoarthritis negative, which we employed to mining features using GLCM and HOG feature extraction techniques. To determine the accuracy, the combined features of GLCM and HOG are then sent to several classifiers. Based on factors including accessibility, reputation, exactness, classification accuracy, and computational difficulty, six pre-trained models— SVM, K- Nearest Neighbor, Decision Tree, Random Forest, Logistic Regression, Naive Bayes are utilized for a thorough investigation. Google Colab provided the computing resources needed to train these models [18]

Dataset Details:

The knee osteoarthritis dataset provided the X-ray images used in this learning process to train the algorithm. The Osteoarthritis Initiative (OAI) organized the photos, which are accessible on Kaggle [18]. The 3,836 knee X-ray pictures in total are separated into datasets for testing, training, and validation. The resolution of each image was 224 × 224 pixels. About half of the dataset contains of normal x-ray, and the other half consists of osteoarthritis positive-ray.

TABLE 2. Sample Images from Datasets

Class	Count of images	X-ray image
Osteoarthritis	2,247	
Normal	1,589	

Data Preprocessing

Data Preprocessing is important in order to provide high-quality input for machine learning models and produces exact and reliable predictions. Also, Normalization and standardization are required for uniformity in medical images which may contain noise. In this Study, Preprocessing processes were applied to the images in each of our three datasets. The goal of the preprocessing stage was to highlight the knee joint and remove extraneous information from the images.

Extraction of Features

A. GLCM (Gray-Level Co-Occurrence Matrix)

Large volumes of data are present along with images; therefore it is essential to extract relevant information from X-ray images. Every pixel in a grayscale image has an intensity value, which usually ranges from 0 indicating black to 255 indicating white, 8-bit pictures. GLCM Feature Extraction inspects the frequency of gray levels occurring together in an image, taking into account nearby pixels. GLCM records the spatial layout of textures by counting co-occurrences in particular directions and pixel offsets. To compute GLCM, three factors are used. The displacement (d) between two pixels comes first. The second is the direction of consideration for pixel pairs, which is usually 0°, 45°, 90°, and 135° (Angle (θ)), and the third is the number of gray levels (G).

For this study, GLCM is a technique used in image handling to extract 24 GLCM features from each image. The calculation of GLCM possessions for different spaces and directions enables the representation of separate texture features within an image. Equations (1) for correlation, (2) for homogeneity, (3) for contrast, (4) for angular second moment (ASM), (5) for Dissimilarity, and (6) for Energy provide the image statistics

Correlation determines how linearly pixel pairings depend on one another. A more consistent texture is indicated by high correlation values.

$$\textbf{Correlation} = \sum_{i=0}^{255} \sum_{j=0}^{255} P(i,j)\,\frac{(i-\mu)(j-\mu)}{\sigma^2} \qquad (1)$$

Homogeneity shows how closely the GLCM diagonal and the element distribution are related. A more uniform texture is suggested by high homogeneity values, which show that the elements are concentrated along the diagonal.

Homogeneity $= \sum_{i=0}^{255} \sum_{j=0}^{255} \frac{P(i,j)}{1+(i-j)^2}$ (2)

Contrast determines how much the image has changed locally. Significant variations between adjacent pixel intensities are indicated by high contrast values.

Contrast$= \sum_{i=0}^{255} \sum_{j=0}^{255} (i-j)^2 P(i,j)$ (3)

Angular Second Moment determines the regularity or homogeneity of an image, in which higher values indicate extra even surfaces.

ASM $= \sum_{i-0}^{255} \sum_{j-0}^{255} [P(i,j)]^2$ (4)

Dissimilarity calculates the average intensity difference between adjacent pixels. Greater textural heterogeneity is directed by high dissimilarity values.

Dissimilarity $= \sum_{i=0}^{255} \sum_{j=0}^{255} |i-j| P(i,j)$ (5)

Energy symbolizes the image's uniformity or orderliness. More consistent texture is indicated by high energy values

Energy $= \sqrt{ASM}$ (6)

B. HOG (Histogram of Oriented Gradients)

Instances of gradient orientation in specific regions of a duplicate are tracked by a feature descriptor known as HOG. After breaking the image up into tiny cells, it computes a histogram of gradient directions inside each cell and normalizes local contrast in overlapping blocks.

Steps for calculating HOG features

Initially In order to determine the angle and magnitude of the gradient, each direction's gradient of pixel intensities is computed. This will ultimately yield the Gx and Gy standards for every pixel. Gx and Gy are used to compute the gradient's magnitude and angle.

Secondly, determine the cell's gradient histogram by dividing copy into cells. Compute a gradient histogram for every cell. The histogram bins represent the discretization of orientations into nine bins, each of which is 20 degrees. Each pixel in the matching bin with a gradient angle has its gradient magnitudes added up. The histogram of each cell will have nine gradient magnitude values.

In third step of Normalize the histogram for Blocks, to compensate for differences caused by varying lighting and noise levels, the histograms are standardized over a wider, overlapping area known as blocks values of gradient magnitude. There may be more than one cell in every block. Concatenate the HOGs of every cell into a single array, and then use L2 Norm to normalize it.

Ultimately, the HOG features from every block in the image are concatenated to make a combined feature vector that characterizes the HOG feature for the entire image. With the size of 8x8 of cell, a block size 2x2 cells, a stride 1 cell, and a histogram with gradient angle bins of 20 degrees, the total number of features with HOG feature extraction for an image of MXM size (M) will be

$\left(\frac{M}{8}-1\right)^2 \times 36$ (7)

Blending of Structures

A mixed feature is produced by combining the structures from HOG and GLCM.

20 features from HOG and 24 features from GLCM make up the total of forty-four features.

Classification

To classify knee x-ray into two groups namely normal or osteoarthritis, machine learning algorithms are fed the data that were taken from GLCM, HOG, and blended features. To categorize x-ray image based on input, many machine learning classifiers are employed, namely SVM, Random Forest, Decision Tree K-Nearest Neighbor, Naïve Bayes and Logistic Regression.

Naïve Bayes

The Bayes theorem asserts that an event's likelihood of occurring is influenced by past knowledge of potential contributing factors. A probabilistic classification technique called Naive Bayes practices the input data to define the likelihood of each class in order to generate predictions[12].

Decision Tree

By reducing the generalization error, decision tree algorithms automatically identify the best choice. It is also possible to define additional target functions, such as minimizing the average depth or the number of nodes[13].

Logistic Regression

A categorical dependent variable and numerous independent variables are compared using logistic regression. Also estimates the likelihood of existence of an occasion by appropriate information to a logistic curve[14].

Random Forest

Random Forest is a flexible process that can be applied in multiclass organization as well as regression and classification difficulties. Random Forests create closeness to impute missing data. Closeness can also provide a wealth of information by enabling new data visualizations[15] .

SVM

SVMs may estimate any multivariate function to any desired level of precision, as is well known. Rather, a learning method based on quadratic programming that results in parsimonious SVMs will be introduced slowly, beginning with linearly separable problems and developing through classification tasks that have classes that overlap but still have a linear parting border [16].

K- Nearest Neighbor

In K- Nearest Neighbor model instances are categorized according to the class of their nearby neighbors. Since including numerous neighbors is regularly beneficial, the method is more often known as k-Nearest Neighbor (k-NN) Classification, where The class is determined by using the k nearest neighbors[17].

Evaluation Metrics

It is essential to evaluate the presentation of machine learning methods before implementing them. Classifiers are typically calculated utilizing F1 scores and classification correctness. The ratio of all correct predictions for all examples in the dataset means classification accurateness. The dataset should be stable in order to derive significant decisions of the model from the classification precision. This is due to the possibility that high amount of accurate estimates in the class with extra models could lead to high classification accuracy on a dataset that isn't balanced. Less weight is given to the classes with lesser examples in the final precision. The F1 score is an additional method for assessing a model's working. The F1 score means harmonic mean of recall and precision. Precision is calculated by dividing the total number of samples classified as positive by the value of properly classified true positives. The model's dependability in classifying samples as positive is established by its great precision. In contrast, the ratio of true positives to the total number of samples in the dataset is recall. High recall identifies that the model can exactly classify positive examples. Equations (8)–(11) display the performance metrics' formulas. Equations (8)–(11) display the formula of performance metrics, provided meaning of TP is true positive, meaning of TN is true negative, meaning of FP is false positive, and meaning of FN is false negative.

The performance of the models was assessed using:

$$\text{Accuracy} = \frac{TN + TP}{TP + TN + FN + FP} \quad (8)$$

$$\text{Precision} = \frac{TP}{FP + TP} \quad (9)$$

$$\text{Recall} = \frac{TP}{FN + TP} \quad (10)$$

$$\text{F1 Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (11)$$

TABLE 3. Results of classifiers Using Feature Extracted from GLCM

Classifier	Training Accuracy value	Precision value	Recall value	f1-score value	Testing Accuracy value	Precision value	Recall value	f1-score value	Validation Accuracy value	Precision value	Recall value	f1-score value
Naive Bayes	0.71	0.75	0.71	0.69	0.67	0.67	0.67	0.62	0.69	0.75	0.69	0.64
Decision Tree	0.79	0.79	0.79	0.79	0.81	0.81	0.81	0.8	0.88	0.88	0.88	0.87
Logistic Regression	0.81	0.81	0.81	0.81	0.75	0.75	0.75	0.74	0.8	0.8	0.8	0.8
Random Forest Classifier	0.83	0.83	0.83	0.83	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
SVM	0.77	0.8	0.77	0.77	0.65	0.68	0.65	0.55	0.77	0.77	0.77	0.76
K-Nearest Neighbor Classifier	0.81	0.82	0.81	0.81	0.75	0.75	0.75	0.75	0.8	0.8	0.8	0.8

Table 3 illustrates results after providing feature extracted from GLCM techniques and applying various training, testing, and validation datasets. The Random Forest Classifier giving remarkable results with high accuracy (88%), perfect recall, precision, and F1-scores on the validation data consistently over others. Decision Tree also performs well, primarily in validation, with the correctness of 88%. Both K-Nearest Neighbor and logistic regression maintain a reasonable level of accuracy (75–80%) across all datasets, indicating a moderate level of performance. Decision Tree and Random Forest are the most reliable classifiers overall, while SVM and other models require additional fine-tuning to improve generalization.

TABLE 4. Results of different classifiers Using Feature Extracted from HOG

Classifier	Training Accuracy value	Precision value	Recall value	f1-score value	Testing Accuracy value	Precision value	Recall value	f1-score value	Validation Accuracy value	Precision value	Recall value	f1-score value
Naive Bayes	1	1	1	1	1	1	1	1	1	1	1	1
Decision Tree	1	1	1	1	1	1	1	1	1	1	1	1
Logistic Regression	1	1	1	1	1	1	1	1	1	1	1	1
Random Forest	1	1	1	1	1	1	1	1	1	1	1	1
SVM	0.96	0.97	0.96	0.96	0.99	0.99	0.99	0.99	0.98	0.99	0.98	0.98
K-Nearest Neighbor	0.94	0.95	0.94	0.94	0.8	0.8	0.8	0.8	0.78	0.78	0.78	0.78

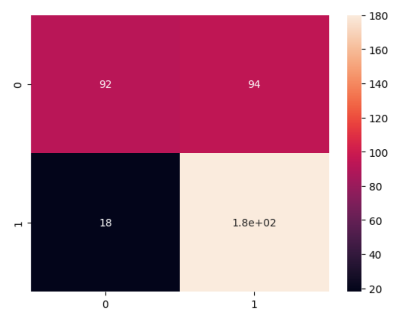
Table 3 is showing results of various training, testing, and validation datasets and feature extraction from HOG techniques. Out of all the classifiers used in this study, Random Forest, Decision Tree, Logistic Regression and Naive Bayes rank highest resulting in to 100% accuracy, precision, recall, and F1-scores. With 96% training accuracy and 99% testing and validation accuracy, SVM performs remarkably well.

TABLE 5. Results of different classifiers after combing Feature Extracted from GLCM and HOG

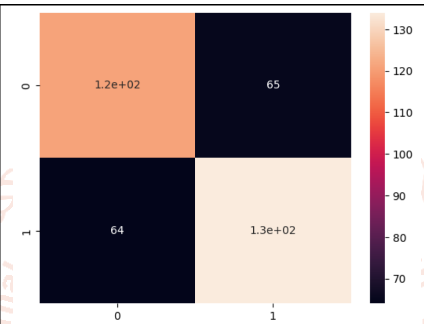
Classifier	Accuracy after combining GLCM and HOG features	Precision value	Recall value	f1-score value
Naive Bayes	0.71	0.84	0.49	0.62
Decision Tree	0.66	0.65	0.65	0.65
Logistic Regression	0.79	0.82	0.73	0.77
Random Forest	0.74	0.75	0.7	0.73
SVM	0.74	0.82	0.6	0.69
K- Nearest Neighbor	0.74	0.76	0.69	0.72

Table 4 showing results for classifiers after applying combined features of GLCM and HOG. Logistic Regression performs well with 79% accuracy rate, 0.82 precision, 0.73 recall, and 0.77 F1-score. Naive Bayes has a high precision of 0.84, lower recall of 0.49 and a moderate accuracy of 71%. Random Forest Classifier, SVM, and K-Nearest Neighbor all attain a comparable 74% accuracy rate. Decision Tree has accuracy of 66% and a stable recall, precision and F1-score of 0.65.

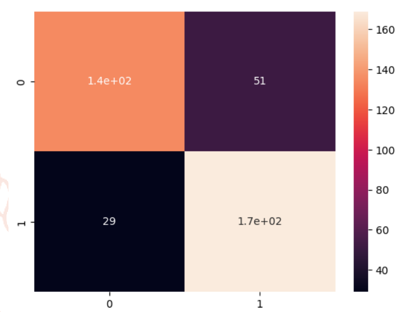
Table 6: Confusion matrices obtained from our models after combing Feature Extracted from GLCM and HOG



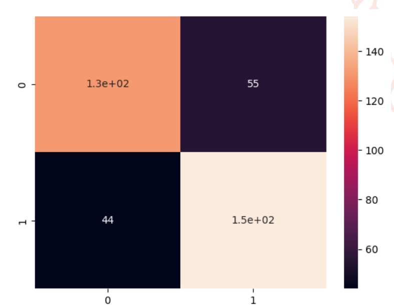
Naive Bayes



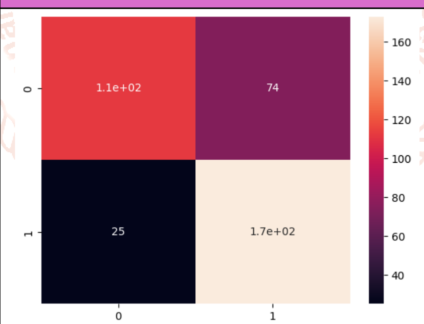
Decision Tree



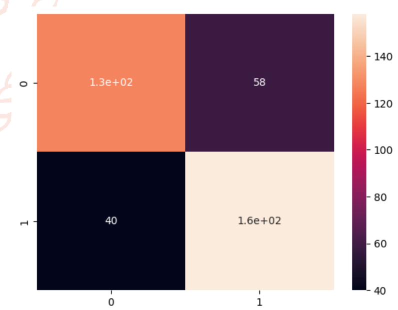
Logistic Regression



Random Forest



SVM



K- Nearest Neighbor

Conclusion

Physicians manually analyze X-ray images, which is laborious, subjective, and unpredictable. It is challenging to carry out an efficient study of X-ray pictures due to the complexity involved. Unwanted distortions in a knee X-ray image can make it difficult to analyze the bone buildings. In order to address these problems, the authors have working an automated technology that offers a rapid and effective way to inspect the variances and problems linked to the bone buildings. The authors have employed various feature extraction techniques on knee x-ray images for this study. The accuracy rates of several classification methods are compared. With the classifier Random Forest, the maximum accuracy amount of 87.92% is attained. Image segmentation procedure or technology must be established in the future to achieve a high classification rate.

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