



# GLCM Based Feature Extraction and Medical X-ray Image Classification Using Machine Learning Techniques

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**Abstract.** The automated system is now created with excellent accuracy to detect abnormalities in X-ray images. To enhance the appearance of medical photographs, image pre-processing methods are applied, so that high accuracy can be achieved with constrained means. Images are often classified based on their textural properties, which are measured using the Gray Level Co-occurrence Matrix (GLCM). The grey level correlation matrix provides statistical information of the second order on the grey levels of neighboring pixels in a picture (GLCM). In this proposed paper, medical X-ray images are classified and their features are extracted using an ensemble learning model. By extracting image features using the GLCM feature extraction method, this proposed model is able to distinguish between healthy and sick images (Gray level co-occurrence matrix).to improve the efficiency of the Ensemble learning classification method, it is compared against various algorithms using performance indicators, including Logistic regression, Gaussian Naive Bayes, as well as Random Forest. When this approach is compared to existing methods, the proposed ensemble model has an accuracy rate of 97% in classifying normal and diseased images.

**Keywords:** GLCM · Machine Learning · random forest · SMOTE

## 1 Introduction

The field of clinical imaging will likely find applications for machine learning as well as artificial intelligence in the not-too-distant future. A number of diagnostic tools, including X-ray machines, magnetic resonance imaging (MRI) scanners, as well as computed tomography (CT) scanners, assist medical professionals in recognizing problems in clinical images more rapidly [1]. Some of the more complex characteristics are utilized to identify things that regular people are incapable of recognizing without the assistance of machine learning as well as artificial intelligence. This new era, marked by the rise of intelligent systems that provide assistance to machines, offers tremendous assistance to radiologists in clinical processes.

Image processing methods play an essential role in medical image interpretation and automated diagnosis. In recent years, the development of whole-slide imaging methods and the rise in cancer cases have attracted the interest of several researchers in image processing. The whole slide photographs have a very high quality, and professionals need a lot of time to weigh in on them [2]. Automated image processing approaches helped by computers are offered to facilitate this exhaustive procedure. These approaches assist the expert in determining the image analysis, and in certain instances take the position of decision maker. The automated categorization of pictures and the decision-making process rely on visual characteristics. Numerous visual characteristics, such as texture variances, shape discrepancies, light fluctuations, and color shifts, offer categorization systems with important information. The most crucial aspect here is to find the right characteristics and classification method for these features. Various feature extraction techniques may provide different categorization outcomes for the same picture. Consequently, feature selection is one of the most crucial steps in classification. Clinical imaging's future applications will include machine learning and artificial intelligence. Some equipment, X-rays, MRI, and CT scans are just a few examples of clinical imaging modalities that help clinicians spot anomalies quickly and accurately. Some of the complex qualities are put to use in order to unearth abnormalities machine learning and AI are required to see this. The radiologist analyses X-ray pictures for bone fracture detection using their training and experience [3]. Automatic anomaly identification of X-ray images assists radiologists in diagnosing a variety of clinical conditions, including arthritis, dental caries, bone cancer, osteoporosis, fracture, as well as infection.

Examining medical pictures is a complex process that calls for a physician's full arsenal of skills, expertise, as well as diagnostic equipment. Clinical X-ray picture anomaly identification via an automatic technique is a challenging problem in machine learning. Patients have wide anatomical variants. As a result, this is a major obstacle when trying to project radiographs that have structures superimposed on top of them [4]. As it is difficult for the medical professional to spot the anomaly due to the low quality of the clinical picture taken by the image capture equipment, a suitable computer-assisted automated detection approach is proposed. Consequently, the radiologist may benefit from automated anomaly identification of X-ray images in the diagnosis of a wide range of clinical issues, including arthritis, dental caries, malignant neoplasm, osteoporosis, fracture, as well as infection.

## 1.1 Computer-Aided Detection (CAD) Systems

Medical image analysis is a complex procedure that calls for a physician's substantial training, experience, and imaging equipment. It is a challenging field of machine learning to develop an automated method for detecting abnormalities in clinical X-ray pictures. The goal of the system is to improve diagnostic accuracy. There is a wide range of anatomical possibilities for each individual patient [4]. As a result, this is one of the most important concerns of radiograph projection, which deals with structures that are overlaid on one another. When fracture detection by X-ray analysis, the radiologist relies on their expertise as well as their experience in the field. Medical professionals may miss an anomaly due to poor image quality from the image capturing device. An efficient automated pc-aided detecting approach has been developed to address this problem.

Therefore, many clinical issues, including arthritis, tooth decay, malignant neoplasm, osteoporosis, fracture, as well as infection, may be identified by the radiologist with the use of automated abnormality detection of an X-ray image. These are only few of the conditions that may be diagnosed.

## **1.2 Musculoskeletal Radiographs (MURA)**

X-rays of the musculoskeletal system are compiled into a huge dataset known as a musculoskeletal radiograph (MURA). To determine if X-ray scans should be considered normal or abnormal, the calculations have to be believed. More than 30 million individuals go to the emergency department every year due to musculoskeletal difficulties; these issues impact upwards of two billion people worldwide and are the major cause of serious, long-term pain and impairment. It is possible that groundbreaking discoveries in medical imaging will be sparked by the MURA dataset, which in turn may analyze the contribution of professionals to the process of social insurance reform. The Medical Image Archive and Registry (MURA) is a major resource for open radiography research that comprises both normal and abnormal X-ray pictures. There are a total of 36770 pictures, 20828 of which are normal X-rays and 15942 of which are abnormal, or 56.64% normal data as well as 43.36% aberrant data, respectively.

## **1.3 Contribution of the Study**

The major focus of this study is on the use of GLCM for feature extraction and ensemble learning for medical X-ray picture categorization. The study explores the possibility of using an ensemble model to detect the normal as well as diseased image.

## **1.4 Objectives of the Study**

The following are the objectives that need to be accomplished in order to do this study. To model an ensemble learning that can be used to detect the normal image and diseased image. To analyze the performance of ensemble learning to classify the images.

## **1.5 Organization of the Paper**

The remainder of paper is structured as follows,

In Sect. 2 the recent work in the medical X-ray image classification and GLCM based features are presented.

In Sect. 3 the proposed methodology is clearly described.

In Sect. 4 the obtained results are presented with a brief discussion.

And finally, the paper is concluded in Sect. 5.

## 2 Literature Review

J. Ding et al. [5] in 2017 we put into place a variety of support vector machines, K-means clustering, as well as a deep learning approach are only few of the machine learning-based techniques. Seventeen GLCM characteristics were used to define these methods, and these were extracted for use in testing and vetting terabytes of image data.

In the year 2018, C. Xia et al. [6] performed using a support vector machine to identify bone tumors from X-ray images based on their texture, as determined by a 5-fold cross-validation procedure. This was done by identifying bone tumors using GLCM-based texture features.

In the year 2019, Z. Xing et al. [7] suggested an enhanced salap swarm technique for optimizing GLCM using a fitness function as well as diagonal class entropy. This algorithm was tested on natural satellite images.

Many of the authors discussed related to medical X-ray image classification and feature extraction by using different methods and algorithms. Some of them are discussed below with accuracy values (Table 1).

**Table 1.** Summarization of literature review

S. NO	AUTHOR	YEAR	PROPOSED METHODOLOGY	RESULT(ACCURACY)
[8]	Pawan Kumar Mall et al.	2019	For the purpose of anomaly identification, LBF SVM (Radial Basis Functions support vector machine), linear SVM (standard), logistic regression (regression with intermediate steps), and decision tree are the four classifiers to choose from	The classification accuracy of the LBF SVM classifier was 62.00%. However, LBF SVM outperforms the other three models significantly, This, considering the visual challenges of identifying factures in the MURA database, is cause for optimism
[9]	Qingchen Zhang et al.	2020	For medical image analytics, a graphics processing unit (GPU) is essential in the field of "smart medicine."	The provided approach improves medical picture classification performance without reducing efficiency compared to conventional architecture and VGG-16
[10]	Basra Jehangir et al.	2022	Chest X-ray images are analyzed using a GLCM-based LGBM classification for the COVID-19 study	The suggested technique was verified by comparing it to the COVID-19 X-ray dataset, as well as an accuracy of 92.40% was obtained
[11]	C.M.A.K. Zeelan Basha	2018	An artificial neural network-based strategy for extracting and classifying statistical features is described	The findings demonstrate that the provided method is an efficient tool for categorising X-ray pictures, with an overall accuracy of 92.3%

## 3 Methodology

The major goal of this study was to create a technique for extracting characteristics from the medical X-ray image and then classifying those features using ensemble learning. Using a feature extraction technique called GLCM, we were able to distinguish between

healthy and sick photos in this research (Gray level co-occurrence matrix). GLCM characteristics that were analyzed in this research are contrast, correlation, dissimilarity, energy, homogeneity.

In this study, there are two classes to examine, those are described below (Figs. 1 and 2):

- Normal
- Disease

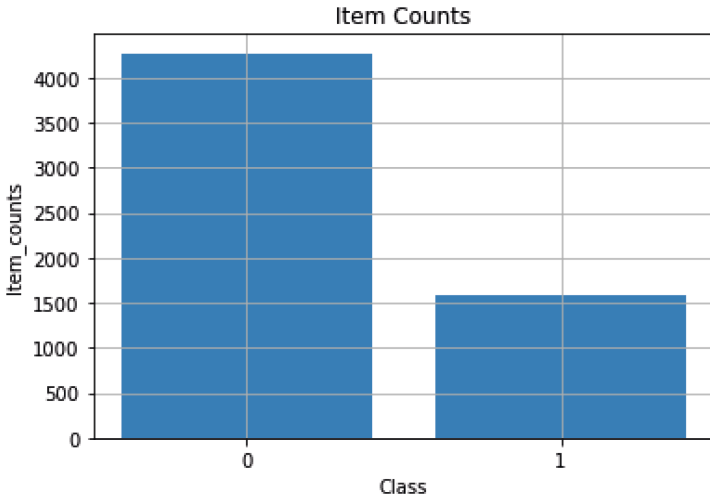


Fig. 1. From the above figure, it is observable that the count of each class is different data.

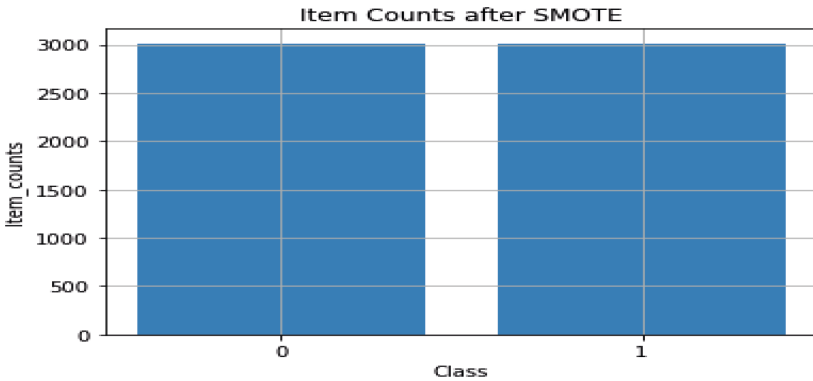


Fig. 2. Counts after SMOTE

For this, we used SMOTE analysis to adjust each and every class with same data.

Finally, Performance measurements are used to compare the Ensemble learning classification algorithm against other algorithms like Logistic regression, Gaussian Naive Bays, as well as Random Forest algorithms in order to demonstrate its effectiveness.

### 3.1 SMOTE Analysis

SMOTE stands for Synthetic Minority Oversampling Technique. SMOTE is an oversampling strategy that involves creating fabricated samples for the underrepresented group. This strategy is useful for avoiding the over fitting problem that might arise from using a large sample size at random. It focuses on the feature space to generate new instances by interpolating between nearby positive examples.

#### Feature Extraction

The process of extracting features from a picture is an essential component of the model that we have suggested. The co-occurrence of neighboring grey levels as well as the counts of those levels in a picture are the basis for the GLCM texture feature, which operates on this phenomenon. The ROI (region of interest) dimension of the a matrix used to compute the GLCM texture feature is set to equal the number of grey levels (N) there in X-ray pictures.

#### 3.1.1 GLCM

The textural characteristic known as GLCM (Gray level co-occurrence matrix) relies on the frequency with which neighboring grey levels appear in a given image. Depending on the number of grayscale values, a square matrix is used to calculate a GLCM texture feature (N) in the area of interest of the X-ray pictures. GLCM is a prominent approach for extracting texture-based features.

This technique uses two metrics to synthesize image features. The GLCM features are calculated during the first step, and the texture properties based on the GLCM are derived during the second process. For a couple of the novel characteristics, the metric formula is illustrated below. The feature is extracted using a grey level co-occurrence matrix.

This investigation made use of the following GLCM characteristics; contrast, correlation, dissimilarity, energy, homogeneity.

#### 3.1.2 GLCM Features

**Contrast:** A metric for determining how often certain parts of an image appear, or the intensity of a pixel and its surrounding pixels, is called contrast. It also establishes how many local differences are visible in the picture. The contrast is calculated by comparing the hue and luminosity levels of the target object to those of other objects in the same visual field. The following equation characterizes the contrast function of any given image:

$$cont. = \sum_i \sum_j |i - j|^2 p(i, j) \quad (1)$$

**Correlation:** A pixel's association with its neighboring pixels throughout the whole picture is measured by an image characteristic called correlation. The correlation coefficient ranges from  $-1$  to  $1$  for properly positively correlated images, and it is infinite for constant images. Equation defines the word "Correl" as the correlation characteristic of a picture.

$$correl = \sum_i \sum_j \frac{(i - \mu_i)(j - \mu_j)p(i, j)}{\sigma_i \sigma_j} \quad (2)$$

**Dissimilarity:** Dissimilarity is a feature that evaluates the distance between two items inside the ROI to determine how different they are. The grey level mean difference in the image's distribution is what this function measures. When the value is bigger, it indicates that the neighboring pixels have a broader range of intensity values to choose from. The characteristic of a picture known as its dissimilarity "Dissimilarity" is defined by the equation as follows:

$$Dissimilarity = \sum_i \sum_j |i - j|p(i, j) \quad (3)$$

**Energy:** When calculating energy, the amount of times a certain set of pixels appears is taken into account. It quantifies how chaotic a picture is. The energy value is quite high for pixels that are strongly connected. The following equation defines the "Energy" attribute of an image:

$$Energy = \sum_{i,j} p(i, j)^2 \quad (4)$$

**Homogeneity:** Inverse distinct movement is the term used to describe homogeneity. With bigger values for lower grey tone differences between paired objects, it evaluates picture homogeneity. With constant energy, homogeneity diminishes as contrast rises. The following equation defines the "Homog" homogeneity characteristic of an image:

$$Homog = \sum_i \sum_j \frac{1}{1 + |i - j|^2} p(i, j) \quad (5)$$

### 3.2 Performance Metrics

Algorithms are evaluated using a variety of performance criteria such as accuracy, sensitivity, precision, and F1-score from the confusion matrix.

**Accuracy:** Rate of accurate identification as a percentage of all subjects.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

**Sensitivity:** Recall measures how many correct labels a computer is able to assign.

$$Sensitivity = \frac{TP}{TP + FN} \quad (7)$$

**Precision:** One way to measure an outlook's reliability is by tallying up the number of correct predictions made thus far. This idea also goes by the name "predictive value".

$$Precision = \frac{TP}{TP + FP} \quad (8)$$

**F1-Score:** Taking into account both precision and recall, the F1-score is a useful measure.

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (9)$$

**Specificity:** In this case, the algorithm made the correct determination that the negative should be labeled as specificity.

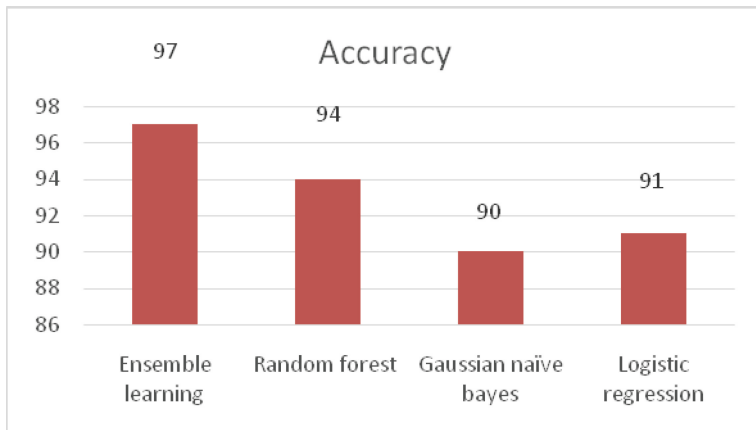
$$\text{Specificity} = \frac{TN}{TN + FP} \quad (10)$$

where,

TP = True Positive  
 TN = True Negative  
 FP = False Positive  
 FN = False Negative

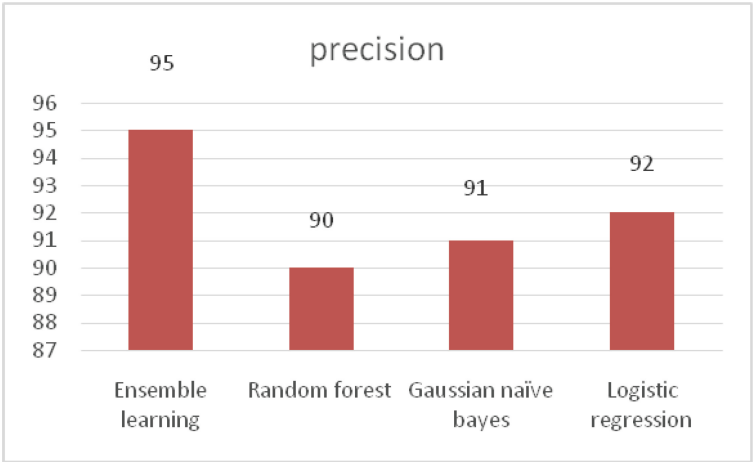
## 4 Results

Measurements of performance are used to evaluate Ensemble learning's classification method against others, such Logistic regression, Gaussian Naive Bayes, as well as Random Forest, to prove the algorithm's efficacy. This comparison is done in order to demonstrate the algorithm's effectiveness (Fig. 3).



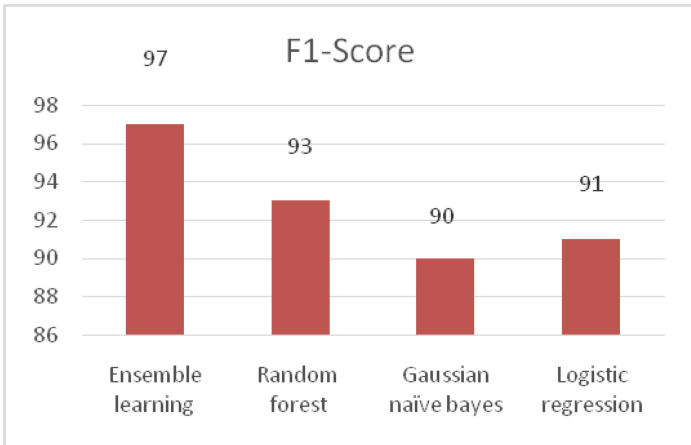
**Fig. 3.** Accuracy analysis of four algorithms

The accuracy analysis of four algorithms is shown in the above figure, with the suggested and existing algorithms on the x-axis as well as the accuracy value on the y-axis. When compared to other methods, ensemble learning with feature selection gives results that are effective (the accuracy value of ensemble learning is 97) (Fig. 4).



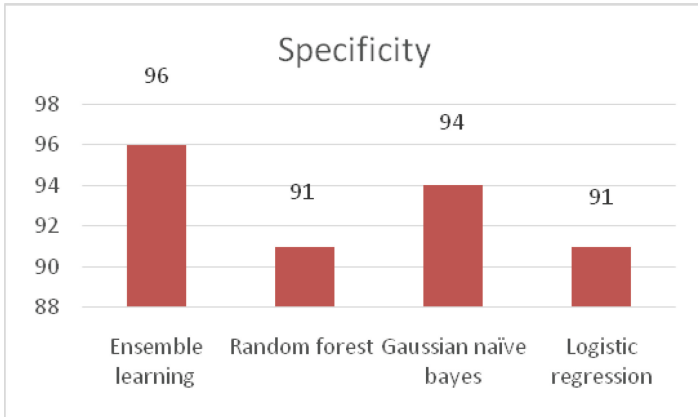
**Fig. 4.** Precision analysis of four algorithms

The precision analysis of four algorithms is shown in the figure above, with the x-axis representing the proposed and current method and the y-axis representing the precision value. The accuracy value of random forest is 90, the precision value of Gaussian naïve bayes is 91, and the precision value of logistic regression is 92. When compared to other algorithms, ensemble learning offers excellent results (Fig. 5).



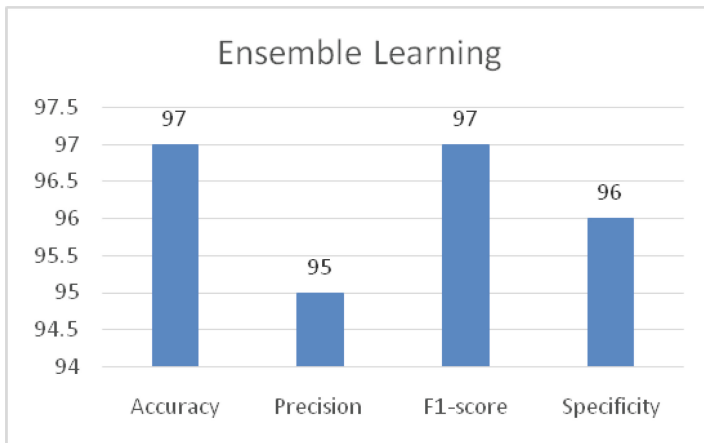
**Fig. 5.** The F1 score analysis of four algorithms

The above figure represents the F1 score analysis of four algorithms with the x-axis being the proposed and existing algorithms and the y-axis being the value of the F1 score. The F1-score value of ensemble learning is 97, It can be concluded that Ensemble learning with feature selection produces effective results when compared with other algorithms (Fig. 6).



**Fig. 6.** Specificity analysis of four algorithms

From the above figure it is observable that the specificity analysis of four algorithms with the x-axis being the proposed and existing algorithm and the y-axis being the specificity value. Random forest specificity value is 91, Gaussian naïve bayes value is 94 and logistic regression specificity value is 91. Ensemble learning produces effective result compared to other algorithms (Fig. 7).



**Fig. 7.** Accuracy, Precision, F1-score, specificity performance parameters

Accuracy, Precision, F1-score, specificity performance parameters (x-axis), parameter values (y-axis), and analyses for ensemble learning are shown above. Ensemble learning's accuracy is 97, its precision is 95, its F-score is 97, and its specificity is 96.

## 5 Conclusion

In the current investigation, Features are extracted from medical X-ray pictures using an ensemble learning model and then classified. Image features are extracted by using a feature extraction approach known as GLCM, we were able to differentiate between normal and diseased images (Gray level co-occurrence matrix). In this investigation, we make use of the following GLCM features: contrast, correlation, dissimilarity, energy, and homogeneity. After extracting the features of an image, SMOTE analysis is carried out to balance the classes. After performing SMOTE analysis, proposed model performance is evaluated by using performance metrics. Performance measurements are used to compare the Ensemble learning classification algorithm against other algorithms like Logistic regression, Gaussian Naive Bayes, as well as Random Forest algorithms in order to demonstrate its effectiveness. Ensemble learning's accuracy is 97, its precision is 95, its F-score is 97, and its specificity is 96. When compared to existing algorithms, the proposed ensemble model was proven to have a 97% accuracy rate in distinguishing between healthy and sick photos.

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