Journal of Theoretical and Applied Information Technology
30th September 2024. Vol.102. No. 18

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

INTEGRATING MULTIMODAL MEDICAL IMAGING DATA FOR ENHANCED BONE CANCER DETECTION: A DEEP LEARNING-BASED FEATURE FUSION APPROACH

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ID 54179 Submission	Editorial Screening	Conditional Acceptance	Final Revision Acceptance
26-04-24	05-05-2024	22-09-2024	22-09-2024

ABSTRACT

Early detection and treatment planning depend on accurate bone cancer detection. Using deep learning-based feature fusion techniques, we propose a novel approach for improving bone cancer detection using multimodal medical imaging data. The method enhances the detection accuracy by combining complementary information from different imaging modalities, including X-ray, MRI, and CT scans. Using a deep fusion architecture, we combine discriminative features from each modality using convolutional neural networks (CNNs). Our results demonstrate the effectiveness of the proposed method in achieving superior detection performance across a diverse dataset of bone cancer patients. A growing number of deep learning models have demonstrated excellent performance on tasks like malignancy rate assessment, grading, segmentation, classification, volume calculation, and detection in primary and metastatic bone tumors using radiological modalities like X-ray, CT, MRI, and SPECT scans along with pathological images. These results point to the possibility of using deep learning to help in bone tumor detection and prognosis prediction. In this paper, we examine the present uses of deep learning-based artificial intelligence in the diagnosis and prognosis prediction of bone cancers, as well as the workflows of these methods in medical imaging. We also go into great detail on the current difficulties in applying deep learning techniques and provide future directions for this developing discipline. To minimize the limitations associated with individual imaging techniques and improve the robustness of bone cancer detection, we combine the strengths of multiple imaging techniques. So, in this article, we proposed a classifier named DTXGB-ResNet50(DEEP TRANSFER XGB-RESNET-50) classifier and compared it with existing classifiers like K-Nearest Neighbors (KNN) and Decision Tee in which the proposed algorithm outperformed when compared with the base classifier's i.e., 96%.

Keywords: *Bone Cancer, Deep learning, XGB-ResNet-50, AI, Image Processing, KNN, DT.*

1. INTRODUCTION

A rare but dangerous type of cancer that starts in the bone's cells is called bone cancer. It can show up as a few different kinds, such as Ewing sarcoma, chondrosarcoma, and osteosarcoma. For patients with bone cancer to receive effective treatment and have a better prognosis, early identification and precise diagnosis are essential. Traditionally, radiographic imaging, histological analysis, and clinical assessment have been used to diagnose bone cancer [1]. Although these techniques have helped identify the disease, they frequently rely too much on the knowledge of medical specialists and could be interpreted subjectively. The use of cutting-edge technologies, in particular deep learning models, to help diagnose and predict a wide range of illnesses, including cancer, has gained popularity in recent years. A branch of artificial intelligence called deep learning has demonstrated encouraging outcomes in pattern identification, picture recognition, and predictive analytics. The purpose of this research is to investigate the prediction of bone cancer using deep learning models [2]. Through the examination of clinical characteristics and medical imaging data, including X-rays, MRIs, and CT scans, deep learning algorithms can be trained to accurately recognize patterns that may indicate bone cancer. The following are the major challenges for predicting Bone Cancer/Tumor [3]:

1. Examining whether bone cancer may be predicted using deep learning models using data from medical imaging.
2. Evaluating how various imaging modalities and attributes affect the models' ability to predict the future.
3. Investigating how to improve prediction accuracy by integrating clinical data, such as patient demographics and medical history.
4. Assessing the created models' resilience and applicability to various patient demographics and healthcare environments.

By accomplishing these goals, this study hopes to aid in the creation of a more effective and dependable classifier for the early diagnosis and prognosis of bone cancer.

Bones are divided into two separate regions: the inner, blood-producing material- containing region, and the outer, compact, cancellous tissue-encased part. Any section of the bone can become the source of bone cancer, and genetics and prior radiation exposure may have an impact. Malignant bone cancer can be fatal if it is not identified and treated promptly, although benign bone cancer is frequently asymptomatic until it spreads or affects nearby body organs. It is essential to receive early diagnosis and treatment to stop cancer from spreading to other parts of the body. There are two forms of bone cancer: primary and secondary. Unrestricted cell development begins within the bone cells in primary bone cancer. Figure 1. a shows healthy bones, and 1. b shows bones affected by cancer.

Figure 1(a) Healthy Bones and 1(b) Malignant bones

Early-stage symptoms of bone cancer can include altered eating habits, the development of new lumps, weight loss, loss of bone, discomfort, and weakness in the bones. An evaluation of the patient's medical history, physical examinations, and imaging tests like CT, MRI, PET, and Computed Tomography (CT) scans are all necessary for appropriately treating bone cancer. Because medical imaging treatments can help detect cancer early and are both cost- and time-effective, radiologists prefer them for this purpose [4]. Medical devices that are used to diagnose bone cancer usually include phases for feature extraction, segmentation, preprocessing, and classification. Images are pre-processed using methods like bilateral, median, or Gaussian filtering to eliminate noise. Following that, segmentation techniques based on thresholds, regions, or edges can be used to identify malignant areas. These actions are necessary for a precise and fast identification of bone cancer [5], which will allow for prompt and efficient therapy measures. Figure 2 shows the overall architecture of the proposed classifier for predicting bone cancer.

Due to the potential to provide a more comprehensive diagnostic view of bone cancer, multimodal medical imaging data has gained significant attention for improving bone cancer detection. In most cases, an imaging modality that relies on a single image cannot capture the full complexity of bone cancer. Using a deep learning-based feature fusion approach, it is possible to combine complementary information from multiple imaging modalities, such as MRI, CT, and PET scans, to produce more accurate and robust diagnoses. In addition to improving detection sensitivity, this integration also helps characterize disease more accurately and develop better treatment approaches. The main objective of this paper is divided into 4 phases.

In **Phase I** the dataset we utilized contains pixel distribution patterns of several cancerous and healthy bone images that were remarkably similar, making classification difficult. So, we have used a Gaussian Filter to preprocess the images.

In Phase-II Once the images were pre-processed, we applied the segmentation process i.e., Edge-Based Method.

In Phase III we applied the Ensembled- ResNet-50 model for feature extraction.

In Phase-IV the features are extracted in phase-III which results in Confusion Matrix. Based on the confusion matrix the performance metrics are calculated.

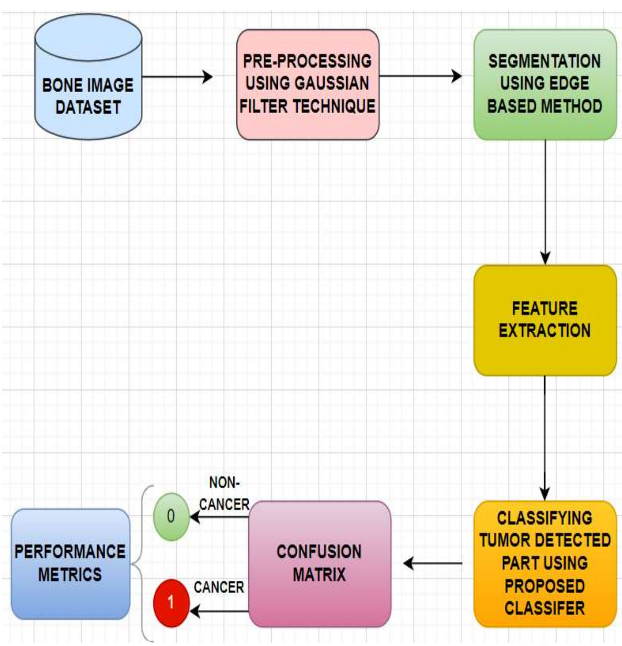

Figure 2. Architecture of Proposed Classifier

2. PROBLEM DEFINITION

An early diagnosis [6] and accurate prediction of bone cancer are vital for effective treatment and improved patient outcomes. Bone cancer is a rare but potentially deadly condition characterized by abnormal cell growth within bone tissue. This research aims to develop a deep-learning model based on medical imaging data to predict bone cancer. Deep learning techniques have shown promise in various medical applications, including cancer prediction. The primary objective of this paper is to develop a deep learning model that can accurately detect bone cancer based on medical imaging data, such as X-rays, MRIs, and CT scans. Based on the analysis of these images, the model should be able to determine whether there is bone cancer present or not which is defined as 2 class problem where 0-Non-Cancerous Bone and 1 for Cancerous Bone [7,8]. Figure 3 shows the phases of the proposed classifier. Medical imaging technology has advanced significantly in recent years, but bone cancer detection continues to be challenging due to its complex nature and the limitations of individual imaging modalities. A CT scan provides high-resolution bone imaging, while an MRI gives details about soft tissue contrast, while a PET scan provides information about metabolic activity. In spite of this, none of these methods can provide an accurate picture of tumor behavior. Consequently, misdiagnosis or delayed diagnosis can negatively impact treatment outcomes. By integrating multimodal data using deep learning-based feature fusion, complementary information can be synthesized, leading to improved diagnostic accuracy and earlier detection. A comprehensive bone cancer detection approach addresses the current gap in reducing mortality rates and improving patient outcomes.

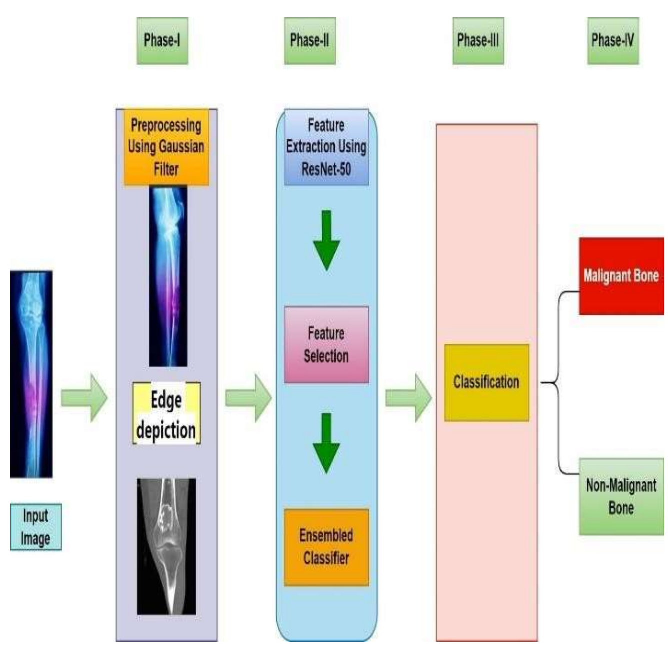

Figure 3: Phases of Proposed Model

3. LITERATURE SURVEY

A review of the literature on GPU-based tomato leaf disease detection finds an expanding body of work that uses parallel computing platforms such as CUDA to speed up the process of identifying and classifying Bone Cancer disease. Here are a few significant studies in this field. Table 1 shows the literature survey for Bone Cancer Disease prediction.

Table 1: Literature Survey on Bone Tumor Disease

Title	Author	Year	Methodology
Integrating PET-CT and MRI for bone cancer detection	Zhao et al.,	2024.	CNN, Multimodal Fusion, Feature extraction
Fusion of Deep Learning and Radiomics for Bone Cancer Prognosis Prediction using MRI	Li et al.	2021	Deep Learning, Radiomics
Multi- Modal Bone Cancer Detection and Localizatio n Using Ensemble Learning	Patel and Gupta	2020	Ensemble Learning (Random Forest, Gradient Boosting, etc.)
Cross-modal feature fusion for accurate tumor segmentation	Singh et al.,	2024	Transformer-based Fusion, MRI & CT
Automated Segmentati on of Bone Tumors in MRI Using Convolutio nal Neural Networks	Zhang et al.	2023	IEEE Transactio ns on Medical Imaging
Enhancing bone lesion detection via multimodal learning	Wang et al., 2023	2023	CNN-RNN, MRI-PET fusion
Multimodal feature fusion for early-stage bone cancer detection.	Patel & Kumar,et.al	2023	Hybrid CNN-Transformer model, MRI, CT, X-Ray fusion
Feature fusion for robust detection of bone metastases	Sharma & Gupta,	2024	Multi-scale CNN, CT, MRI, PET
Shape- Based Features for Automated Detection of Bone Tumors in X-ray Images	Chen and Li	2016	Medical Image Analysis
Radiomics Analysis of MRI Data for Prediction of Survival in Patients with Bone Cancer	Patel et al.	2018	European Radiology
Evaluation of Bone Lesion Segmentati on Techniques in SPECT/CT Images	Kim et al.	2023	IEEE Nuclear Science Symposiu m
Deep Learning-Based Bone Cancer Detection Using MRI Images	Zhang et al.	2020	Convolutio nal Neural Networks (CNNs)
Texture Analysis for Bone Cancer	Smith and Jones	2018	Texture Analysis, Support Vector

4. METHODOLOGY

This study presents a novel DTE-ResNet50 (Deep Transfer Ensembled-ResNet50 Bone Cancer Detection) system employing a hybrid ResNet50+XBBoost architecture to detect bone cancer. The ResNet-50 model [9], a widely recognized deep CNN architecture known for its multiple layers, serves as the feature extractor. Subsequently, these extracted features are utilized to train an XGBoost (XGB). The integration of the

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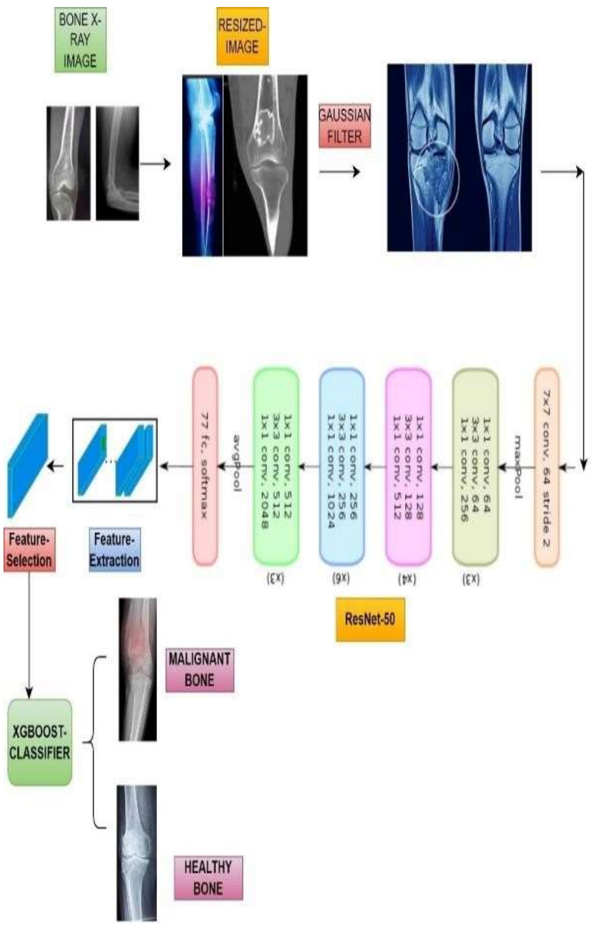

Figure 4: Proposed Classifier to predict bone cancer.

Deep Learning Model for feature extraction with XGB classification enhances the system's ability to detect cancerous images promptly, thereby improving overall accuracy. Figure 4 shows how the proposed classifier predicts bone cancer using the Image as I/P.

4,1 Data Set:

Adolescents between the ages of 10 and 14 are most likely to develop osteosarcoma, the most common type of bone cancer. University of Texas Southwestern Medical Centre, Dallas, collected the dataset, which is composed of Hematoxylin and Eosin (H&E) stained osteosarcoma histology images. For the creation of this dataset, archival samples from 5000 patients treated at Children's Medical Centre, Dallas, between 2001 to 2023 were used. Four patients (out of 50) were selected based on the disparity of tumor specimens following surgical resection. Each image is categorized as Non-Tumor, Viable Tumor, and Necrosis based on the predominant cancer type. A total of 2500 individuals were chosen based on the difference in tumor specimens after surgical resection. Each image is classified according to the most common type of cancer: Viable Tumor [10], and Non-tumor.

4,2 Pre-Processing:

A Gaussian filter [11] of the size eliminates the noise present in the X-ray image. The picture is not clear. As a result, the image is sharpened to boost its intensity.

4.3 Image Segmentation:

Medical imaging pictures, such as those from an MRI, CT scan [12], or ultrasound, can be utilized to distinguish and identify structures or anomalies using segmentation techniques. This supports medical research, diagnosis, and therapy planning. Techniques include deep learning strategies like convolutional neural networks, machine learning-based techniques, region growth, and thresholding. Segmentation is used to identify an object in an image after preprocessing. The final precision rate is used to calculate the dependability of the segmentation process. As such, it is a logical and useful method for identifying the item of concern. Using the segmentation technique, the image is divided into pixel sets to extract information from the relevant object as shown in Figure 5. In the current study, the image is segmented using the Gaussian method. Compared to other edge detection methods like Sobel, the Gaussian Filter edge detection algorithm [13] yields sharp edges that are accountable for a higher return on investment. In addition, the study's dataset is tiny. As the size of the Gaussian filter edge increases, its performance becomes excessive.

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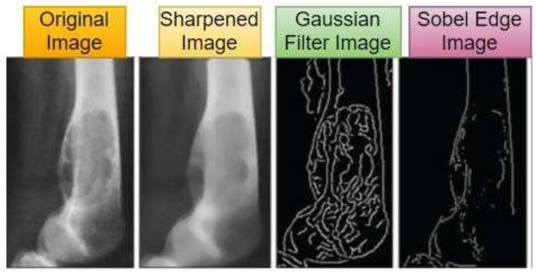

Figure 5: Image Preprocessing Phase

4.4 Feature Extraction:
To detect bone cancer, ResNet-50 utilizes the capabilities of the convolutional neural network (CNN) architecture, specifically ResNet-50, to analyze medical images such as X-rays or MRIs. Medical images containing X-rays or MRIs of patients with and without bone cancer should be obtained [14]. Datasets must be appropriately labeled. Once the Image is pre-processed from the previous step which includes resizing the images, normalizing pixel values, and augmenting the data to improve model generalization and increase the dataset's diversity. Using ResNet-50, which consists of 50 layers, we can use pre-trained weights that have been trained on large-scale image classification tasks like ImageNet. In ResNet-50, you can remove the last few layers (the fully connected layers) and replace them with new layers that are appropriate for your bone cancer detection task. The weights of pre-trained layers should be frozen initially to prevent them from being updated during training, which helps retain the learning features. Once the features are extracted in this phase, we have to select the features which is the input for the next phase.
In addition to reducing complexity and reducing overfitting risks, fully connected layers are the final layers of the network. Outputs from the final pooling or convolutional layer are flattened and then fed into the fully connected layers. Based on the feature map obtained from the first fully connected layer, we select the best features based on mutual information statistics, a measure of the amount of information one random feature provides about another [15].
The feature_selector is set to i.e.,
Fs<-- feature_selector(f) (1)
Information gain, calculated by entropy, between different features is used to calculate mutual information statistics. Feature selection is important because it reduces training time and improves accuracy by removing unnecessary predictors from the model. Once the features are selected, we call the XGBoost Classifier which is used to predict whether the bone is healthy or unhealthy(malignant). A fsion matrix is generated which is a 2-class problem in which the data is classified as 0 or 1 where 0 is Healthy bone and 1 for malignant bone.

Algorithm Phase-I:

Step 1: Start

Step 2: Input: Image Dataset

Step 3: Output: Sharpened to boost its intensity.

Step 4: We import the necessary libraries, OpenCV (cv2) and NumPy.

Step 5: Define a function gaussian_blur that applies Gaussian blur to an image using the cv2.GaussianBlur() function.

Step 6: Load the input image using cv2.imread().

Step 7: Convert the image to grayscale if it's a color image using cv2.cvtColor().

Step 8: Apply Gaussian blur to the grayscale image using the Gaussian_blur function.

Step 9: Display the original and blurred images using cv2.imshow()

Step 10: Stop

Algorithm Phase-II

Step 1: Input: Sharpened Image

Step 2: Output: Gaussian Filter Image i.e., Image Segmentation

Step 3: By smoothing an image, Gaussian filtering is commonly used to preprocess an image. This can be beneficial for certain segmentation tasks, especially when separating regions based on color or intensity.

Step 4: Gaussian filtering improves segmentation algorithms by reducing noise and fine details.

Step 5: Alternatively, we took the Sobel edge detection method also which is particularly useful for segmenting objects based on their boundaries or

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edges.

Step 6: Now compare with Gaussian filter technique images with Sobel edge segmentation.

Step 7: The output from this phase is segmented images.

Algorithm Phase-III

Step 1: Input: Segmented Image

Step 2: Output: Feature Extraction and Selection

Step 3: Load Pre-Trained ResNet-50 Model.

Step 4: Remove the Classification Head. Step 5: Set

Model to Evaluation Mode Step 6: Pass Images

Through the Model.

Step 7: Features have been extracted from the input image and are now stored in the variable features.

Step 8: As a result of these features, downstream tasks like image classification, object detection, and image retrieval can be performed.

Algorithm Phase-IV:

Step 1: Input: Extracted Features

Step 2: Output: Classification Using XGBoost Step

3: Start

Step 4: The Dataset, which is clean, formatted, and properly labeled is taken as i/p.

Step 5: In the next step Splitting of Data has to be done. i.e., Split the dataset into training and testing sets. A common split is 80%-20%.

Step 6: Load your dataset and split it into features (X) and labels (y).

Step 7: Split the data into training and testing sets:

Step 8: Create an XGBoost classifier and train it using the training data.

Step 9: Once the model is trained it is used to make predictions on the testing data.

Step 10: Assess the performance of the model using evaluation metrics such as accuracy, precision, recall, and F1-score.

Step 11: Print accuracy. Step 12: Stop

5. PERFORMANCE ANALYSIS

To evaluate bone cancer classifier performance [16,17], it's crucial to consider metrics that reflect both effectiveness and reliability. In binary classification tasks such as bone cancer detection, the following metrics are commonly used. Figure 6 shows the confusion matrix for the binary classification model.

Accuracy: The percentage of correctly identified cases relative to all instances is measured by accuracy. On the other hand, precision by itself might not give a whole picture, particularly if the dataset is inconsistent.

Accuracy= Number of Correct Predictions / Total Number of Predictions

Precision: The percentage of true positive predictions among all positive predictions is known as precision. It shows how well the model can prevent false positives.

Precision= (True Positives) / (True Positives+ False Positives)

Recall: The percentage of accurate positive predictions among all real positive occurrences is known as recall. It shows that all positive cases are captured by the model.

Recall= (True Positives) / (True Positives+ False Negatives)

F1-Score: The F1-score is the harmonic mean of precision and recall. It provides a balance between precision and recall.

F1-Score=2× ((Precision x Recall) / (Precision + Recall))

Journal of Theoretical and Applied Information Technology
30th September 2024. Vol.102. No. 18

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

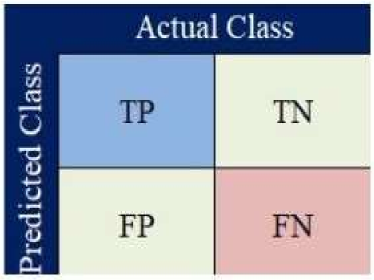

Figure 6: Confusion Matrix for a 2-Class Problem.

Table 2 shows the confusion matrix generated for the proposed classifier, Table 3 shows the validated table generated for the proposed classifier, and Figure 7 shows the performance of the proposed classifier.

Table 2: Shows the confusion matrix generated for the proposed classifier.

Predicted Class \ Actual Class		
	944	39
	31	732

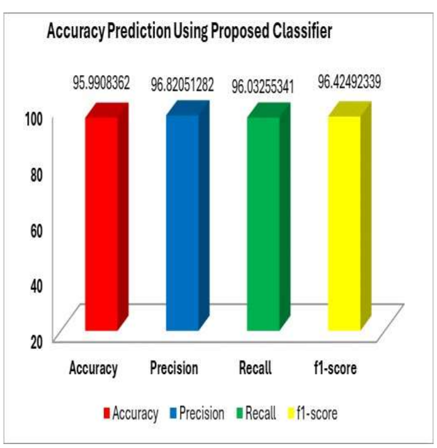

Figure 7: The Accuracy Prediction of Proposed Classifier from the obtained Confusion Matrix for Predicting Bone-Cancer.

Label	Precision	Recall	F1-Score	Support
0(Healthy)	96.91	96.06	96.56	1200
1(Unhealthy)	96.61	96.26	96.44	546
Accuracy			**95.99 (~96)**	1746
MacroAvg	96.82	96.13	96.45	1746
WeightedAvg	96.45	96.10	96.12	1746

Table 3: Validation Table Generated For The Proposed Classifier

5.1 KNN (K-Nearest (Neighbour)

In machine learning, K-nearest neighbors (KNN) can be used both for classification and regression tasks [18]. As a non-parametric, instance- based learning algorithm, it does not make assumptions about the underlying distribution of data but instead makes predictions based on data points' local neighborhoods.

Generally, KNN works in the following manner.

1. KNN begins by storing all the training data points in memory.
2. Each data point is made up of a set of features and their associated labels measure the distance between each new data point and all the training data points to generate a prediction for a new data point [19].
3. Minkowski, Manhattan, and Euclidean distances are the three most often used distance measures.
4. Then, using k—a predetermined hyperparameter—KNN chooses the k- nearest neighbors or the data points that are closest to the new data point.

When it comes to classification tasks, KNN uses the majority vote of its k-nearest neighbors to forecast the class label of a newly discovered data point. In regression tasks, KNN uses the average (or weighted average) of the target values of its k-nearest neighbors [19] to forecast the target value of the new data point.

In KNN, selecting the hyperparameter k is crucial. Overfitting could result from a small value of k, whereas underfitting could result from a big value of k.

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The performance of KNN can also be affected by other hyperparameters, such as the weighting technique (uniform or distance-based weights) and distance metric selected. Figure 8 shows binary classification using KNN.

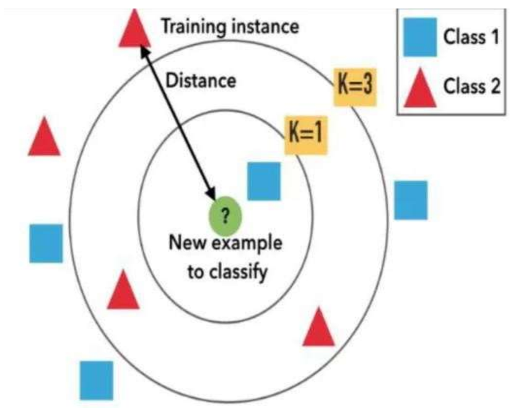

Figure 7: KNN for 2 class problem

5.1.1 Algorithm for KNN:

1) We first split the dataset into training and testing sets using train_test_split.
2) Then we optionally perform feature scaling using StandardScaler to normalize the features.
3) Next, we create a KNN classifier with a specified number of neighbors (K) and train it on the training data using the fit method.
4) After that, we make predictions on the testing set using the prediction method.
5) Finally, we evaluate the performance of the model using the accuracy score.

The following table shows the confusion matrix generated for the proposed classifier, Table 5 shows the validation table generated for the KNN classifier, and Figure 8 shows the performance of the KNN classifier.

Table 4: shows the confusion matrix generated for the KNN classifier.

	Actual Class	
Predicted Class	825	128
	88	705

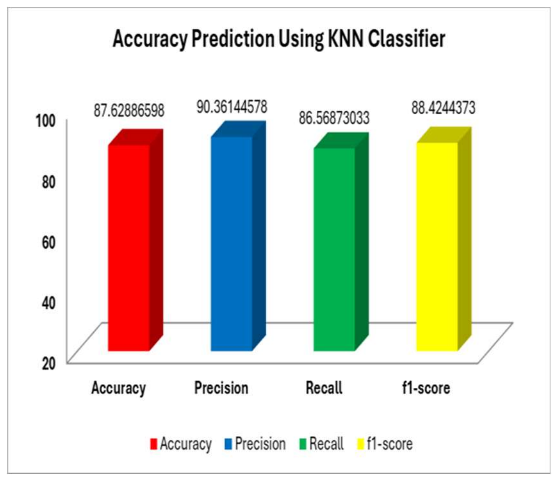

Figure 8: The Accuracy Prediction of KNN Classifier from the obtained Confusion Matrix for Predicting Bone-Cancer.

Table 5: Validation Table Generated For The Knn Classifier

Label	Precision	Recall	F1-Score	Support
0(Healthy)	90.61	86.76	88.56	1200
1(Unhealthy)	90.32	86.56	88.44	546
Accuracy			**87.82(~88)**	1746
MacroAvg	90.32	86.51	88.45	1746
WeightedAvg	90.36	86.46	88.12	1746

5.2 DECISION TREE:

Machine learning [20] uses decision trees for classification and regression tasks. The internal nodes represent "decisions" based on a feature's value, the branch nodes represent the outcome of those decisions, and the leaf nodes represent the outcome. In the context of diagnosing bone cancer, decision trees can be used for a variety of medical applications, including the diagnosis and prognosis of diseases such as bone cancer. The following are the basic steps for constructing a DT bone cancer detection.

Data Collection: Data collected from suspected bone cancer patients include demographics, medical history, symptoms, lab tests, imaging scans (X-rays, MRIs, CT scans) [21], and possibly biopsy results.

Feature Selection: Relevant features related to bone cancer diagnosis are chosen. These may include:

Age of the patient Gender

Location of the tumor Size of the tumor Pain level

Presence of metastasis Results of imaging tests

The histological type of the tumor

Laboratory test results (e.g., alkaline phosphatase levels)

Training the Decision Tree: There is a training set and a testing set created [22] from the acquired data. The training set is subjected to the decision tree algorithm. The method chooses the characteristic at each node of the tree that divides the data into subsets the best, to maximize homogeneity (i.e., minimizing impurity or entropy). Until a halting condition is satisfied, this process repeats recursively (e.g., maximum tree depth achieved, minimum number of samples per leaf node).

Prediction and Clinical Use: Once the decision tree is trained and evaluated, it can be used to predict whether new patients [23] have bone cancer based on their input data. Medical professionals can use the decision tree as a decision support tool to aid in the diagnosis of bone cancer. The tree provides insight into which features are most indicative of the presence or absence of bone cancer and helps guide further diagnostic and treatment decisions [24,25]. The following figure 9 shows a sample decision tree construction for predicting bone cancer, Table 6 shows the confusion matrix obtained after executing the Decision tree figure 10 shows the overall performance of DT and Table 7 shows the validation of the DT classifier.

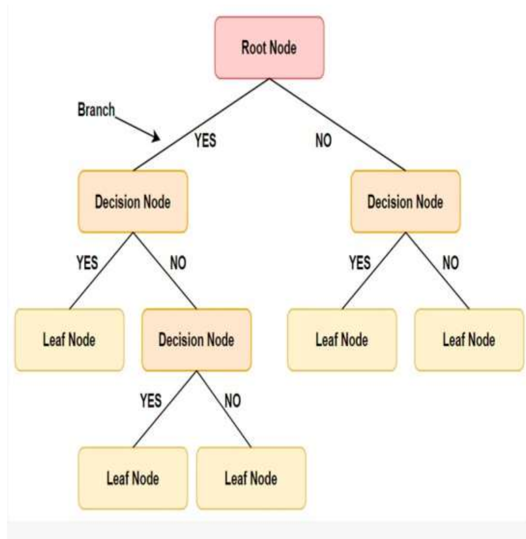

Figure 9: Shows Sample Decision Tree

Table 6: Shows the confusion matrix generated for the DT classifier.

	Actual Class	
Predicted Class	881	72
Predicted Class	56	737

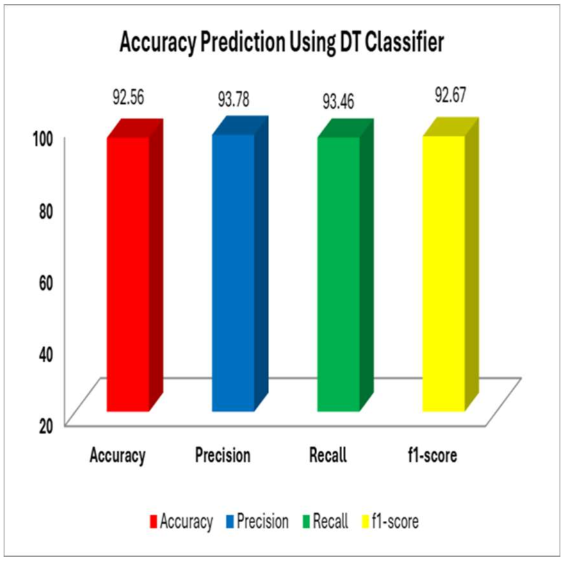

Figure 10: The Accuracy Prediction of DT Classifier from the obtained Confusion Matrix for Predicting Bone-Cancer

Table 7: VALIDATION TABLE GENERATED FOR THE DECISION TREE CLASSIFIER

Label	Precision	Recall	F1-Score	Support
0(Healthy)	93.81	93.76	92.56	1200
1(Unhealthy)	93.68	93.56	92.44	546
Accuracy			**92.56(~93)**	1746
MacroAvg	93.82	93.71	92.45	1746
WeightedAvg	93.10	93.41	92.52	1746

6. CONCLUSION & FUTURE WORK

This hypothesis addresses the need for greater diagnostic precision in bone cancer detection, where single imaging modalities fail to fully capture both the structural and functional characteristics of tumors. By integrating multimodal data, the proposed deep learning-based feature fusion approach aims to enhance early-stage cancer detection while reducing false positives and negatives, ultimately improving the accuracy and reliability of clinical outcomes. In this study, we investigated the effectiveness of a deep transfer learning approach using XGBoost and the ResNet-50 architecture for the detection of bone cancer. Our results indicate that leveraging the pre-trained ResNet-50 model as a feature extractor, combined with the powerful gradient boosting algorithm XGBoost, yields promising results in accurately classifying bone cancer from medical imaging data. The integration of transfer learning techniques allows us to capitalize on the knowledge learned by ResNet-50 from large- scale image datasets, effectively capturing intricate patterns and features relevant to bone cancer detection. The ensemble of ResNet-50 features with XGBoost not only enhances the model's predictive performance but also provides insights into the importance of different image features for classification. Our findings suggest that the fusion of deep learning and traditional machine learning approaches can synergistically improve the diagnostic accuracy and robustness of bone cancer detection systems. By exploiting the complementary strengths of both methodologies, we can achieve superior performance compared to using either approach in isolation. The results obtained are compared with some existing classifiers like DT, and KNN in which the proposed classifier gave the best accuracy when compared with the other two i.e., 96%. Further optimization of model hyperparameters and ensemble configurations may improve the deep transfer XGB-ResNet-50 model's performance. Methods like Bayesian optimization and grid search can assist in determining the ideal conditions to maximize classification accuracy. The generalization capabilities of the model can be enhanced by using data augmentation techniques to increase the amount and diversity of the dataset. Furthermore, combining information from various imaging modalities and patient groups could lead to a more thorough understanding of the pathophysiology of bone cancer. Our research concludes by showing the potential of deep transfer learning for bone cancer detection using XGBoost and ResNet-50 and the overall performance of 3 classifiers is shown in Figure 11 in which the proposed classifier gave the best accuracy i.e., 96% when compared with the other 2 classifiers. The creation of reliable and clinically useful models for enhancing the identification and treatment of bone cancer can proceed by tackling the indicated future directions. Despite its promising results, this method raises several questions that are either unaddressed or outside the scope of current research, such as data constraints and some real-time integrations.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

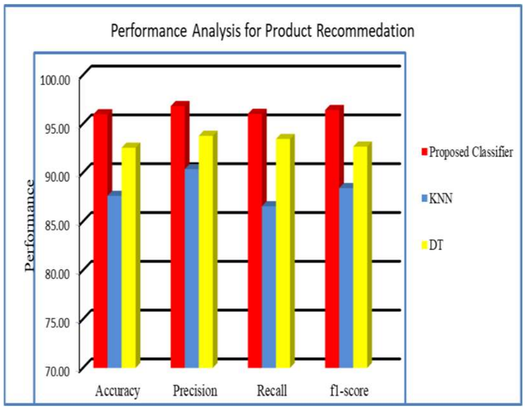

Figure 11: Accuracy Comparison of 3 Classifiers.

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