IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Bone Cancer Detection Using Convolutional Neural Network

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Abstract: Bone cancer is a serious medical condition that develops when abnormal cells grow uncontrollably within the bone. It can originate in the bone (primary bone cancer) or spread from other organs (secondary or metastatic bone cancer). Causes include genetic mutations, exposure to radiation, and underlying bone disorders like Paget's disease. People suffering from bone cancer often endure intense pain in the affected area, along with swelling, tenderness, and sometimes visible lumps. As the cancer weakens the bone, fractures can occur even with minor injuries. Many patients experience fatigue, weight loss, and a general sense of illness, which can make daily activities difficult. Bone cancer may affect individuals at any age but commonly appears in children, teenagers, and adults. It often goes undetected in its early stages due to vague symptoms such as pain or swelling, leading to delayed diagnosis and treatment.

This proposes a method for the detection of bone cancer using Convolutional Neural Networks (CNNs) and aiming to improve early diagnosis. CNNs are powerful deep learning models capable of identifying patterns in complex data, such as medical images. By training the model on bone scan images or related diagnostic visuals, it can learn to recognize signs of cancerous growth with high accuracy. This approach provides a fast, cost-effective, and non- invasive tool to assist doctors in diagnosing bone cancer at an early stage, potentially improving patient outcomes and survival rates.

Index Terms – Bone Cancer, Convolutional Neural Network, MATLAB, Image Processing, Deep Learning, Medical Imaging

I. INTRODUCTION

Bone cancer detection is a critical area in the field of medical diagnostics, where early detection can significantly impact the patient's prognosis. Bone cancer, although less common compared to other types of cancer, can be aggressive and often diagnosed at later stages. The project focuses on developing an automated system for detecting bone cancer, leveraging modern technologies like machine learning, artificial intelligence, and medical imaging. Bone cancer, though relatively rare compared to other forms of cancer, remains a significant medical challenge due to its aggressive nature and the complexity involved in early diagnosis. It occurs when abnormal cells in the bone tissue grow uncontrollably, potentially spreading to other parts of the body. Early detection of bone cancer plays a critical role in improving patient outcomes, as timely treatment can prevent the cancer from advancing to more severe stages. Detecting bone cancer often involves various medical imaging techniques, such as X- rays, CT scans, and MRIs, which are used to identify abnormalities like bone lesions, fractures, or unusual growths. However, interpreting these images requires expert knowledge, and the process can be time-consuming and prone to human error. Advancements in artificial intelligence (AI) and machine learning (ML) present significant opportunities for improving the accuracy and efficiency of bone cancer detection. By leveraging deep learning models, particularly convolutional neural networks (CNNs), it is possible to automate the analysis of medical images, enabling early and more accurate identification of bone cancer. These technologies can aid healthcare professionals by providing them with a reliable second opinion, reducing diagnostic delays, and ultimately leading to better patient outcomes. This document outlines the key technologies, methodologies, and phases involved in the development of a bone cancer detection system, providing a comprehensive overview of the project's scope and objectives. Through this innovation, the project aims to contribute significantly to the field of medical diagnostics, particularly in the early detection of bone cancer. The goal is to create a tool that not only enhances the diagnostic process but also helps in the early detection of bone cancer, improving the chances of successful treatment and recovery.

II. LITERATURE REVIEW

1. Zhang et al. (2021): Multimodal Data Integration for Diagnosis

Zhang et al. (2021) introduced a multimodal diagnostic approach, incorporating not just imaging data but also genetic markers and clinical features. Their work showed that integrating diverse data types helps machine learning algorithms identify complex disease patterns and improve diagnostic accuracy. By combining genomic, radiological, and clinical information, the models provided a more comprehensive understanding of bone cancer progression.
Some of the key drawbacks include:

- **Data Availability and Integration Challenges**: Collecting and harmonizing diverse data types (e.g., genomic, imaging, and clinical records) is often difficult due to inconsistent data formats, missing information, and limited accessibility in clinical settings.

- **High Computational Requirements**: Multimodal models require advanced infrastructure and significant computational power to process and analyze large, heterogeneous datasets efficiently.

2. Shen et al. (2019): Deep Learning for Bone Cancer Detection

Shen et al. (2019) explored the application of deep learning models, especially CNNs, in detecting bone cancer from X- ray and MRI images. Their research revealed that these models can identify subtle features in medical scans that may be overlooked by radiologists. This significantly reduces diagnostic errors and enhances early detection rates.

- In medical imaging, acquiring such datasets is difficult due to privacy concerns, labeling costs, and limited availability of rare conditions like bone cancer.

3. Esteva et al. (2019): AI in Early Disease Detection

Building upon previous research, Esteva et al. (2019) demonstrated that deep learning models could rival expert-level performance in identifying early signs of diseases from medical images. Their findings support the integration of AI into diagnostic pipelines to boost precision and minimize false negatives, particularly in complex imaging cases.

III. EXISTING METHOD

1. Aftab et al. (2023): Predictive Modelling Using Integrated Multimodal Data

Aftab et al. developed a deep learning-based predictive model that integrates clinical data, radiological imaging (X- rays, CT, MRI), and genetic information. By using Convolutional Neural Networks (CNNs) and advanced data fusion techniques, the model achieved high sensitivity and specificity, especially for detecting early-stage and hard-to- identify tumors.

Drawbacks:

- Data Integration Challenges: Combining multiple data types increases the complexity of model development.
- High Resource Demand: Requires substantial data preprocessing, storage, and computational infrastructure.

2. Dr. Krishnan et al. (2021): Bone Cancer Classification Using Decision Trees and Ensemble Methods

Dr. Krishnan and team proposed a classification framework to distinguish benign from malignant bone tumors using features like clinical symptoms, tumor size, and anatomical location. Among the algorithms tested, ensemble methods such as Random Forests provided superior performance compared to standalone decision trees. They offered higher accuracy, model stability, and reduced risk of overfitting.

Drawbacks:

- Interpretability Issues: Ensemble models like Random Forests, while accurate, function as “black boxes” and offer limited transparency.
- Model Complexity: Increased computational complexity and resource requirements compared to simpler classifiers.

3. Dr. Smith: Role of Bone Marrow Biopsy in Bone Cancer Detection

Dr. Smith’s foundational work emphasized the role of bone marrow biopsy in the detection and staging of metastatic bone cancers. His research provided crucial insight into how bone marrow infiltration reflects disease progression, especially in secondary bone cancers from primary sites like the breast, prostate, and lungs.

4. Dr. Green: Molecular and Pathological Insights into Bone Cancer

Dr. Green focused on the molecular biology and pathology of bone cancers, particularly osteosarcoma. His work contributed to the understanding of genetic mutations, tumor microenvironments, and the biological pathways involved in cancer progression.

IV. PROJECT METHODOLOGY

4.1 BLOCK DIAGRAM OF PROPOSED SYSTEM

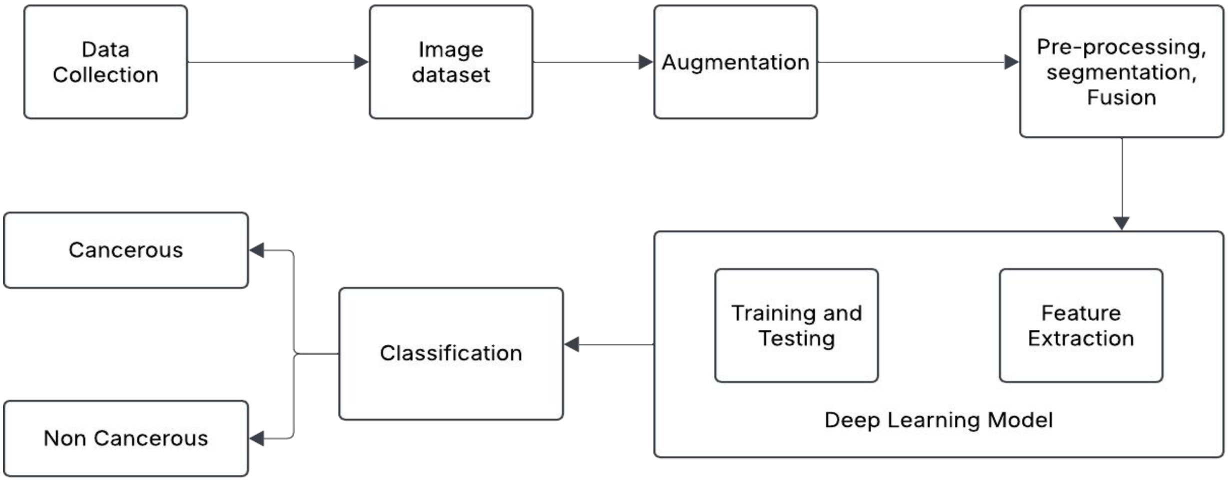


FIG 4.1 BLOCK DIAGRAM OF PROPOSED SYSTEM

BLOCK DIAGRAM DESCRIPTION

The proposed system is a deep learning-based medical image classification framework for detecting cancerous and non- cancerous cases. It starts with DATA COLLECTION, where medical images (e.g., MRI, CT scans, histopathological slides) are gathered and labeled as cancerous or non-cancerous. The images undergo AUGMENTATION techniques like rotation, scaling, and contrast adjustment to improve model generalization. Alex Net, a deep convolutional neural network, is utilized for feature extraction during this process, enhancing the model's ability to identify subtle differences between cancerous and non-cancerous tissues.

Next, the images undergo PRE-PROCESSING, SEGMENTATION, and FUSION. Pre- processing removes noise and enhances contrast, while segmentation isolates the region of interest (ROI). Fusion may combine multiple imaging modalities, like MRI and PET scans, to provide richer diagnostic insights. These steps ensure that only the most relevant features are used for classification.

The refined images are processed using FEATURE EXTRACTION by Alex Net and other CNN architectures to identify patterns like shape and texture. The model undergoes training and testing using labeled examples,

fine-tuning Alex Net for optimal performance.

After training, the system classifies images as **CANCEROUS or NON-CANCEROUS**, improving diagnostic accuracy, efficiency, and aiding healthcare professionals in early cancer detection and treatment planning.

4.2 FLOW CHART

FLOW CHART DESCRIPTION

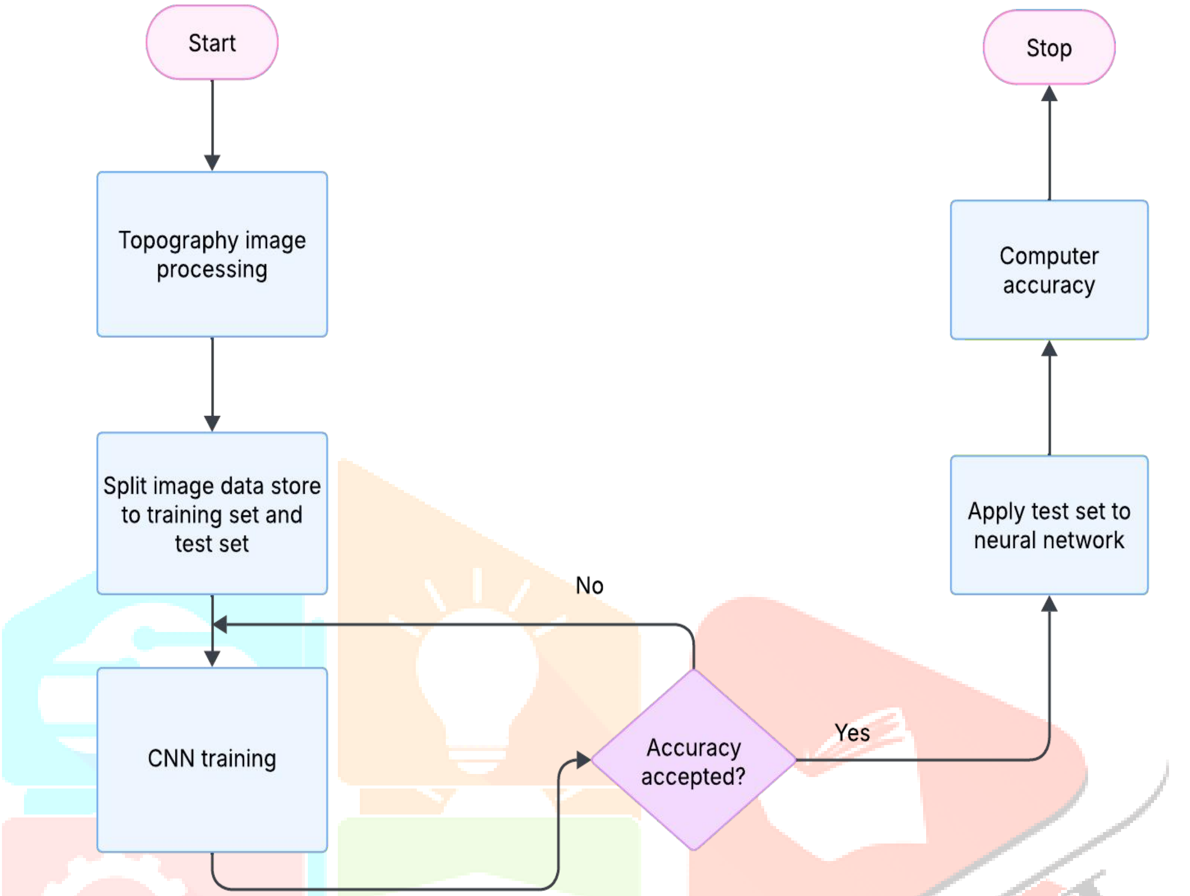


FIG 4.2 FLOW CHART OF THE PROPOSED SYSTEM

The flowchart represents a Convolutional Neural Network (CNN)-based image classification workflow, particularly focusing on topography image processing for training and evaluation.
It outlines a structured approach to processing images, training a deep learning model, validating accuracy, and assessing the final classification performance.

1. **Start**

The process begins with an initialization step, indicating the start of the CNN-based image classification pipeline.

2. **Topography Image Processing**

The collected images go through pre-processing techniques such as:
Noise reduction
Contrast enhancement
Normalization
Edge detection
This step ensures that the input data is suitable for training the CNN model.

3. **Split Image Dataset into Training and Testing Sets**

The dataset is divided into two parts:
Training Set: Used to train the CNN model to recognize patterns and features in the images. Testing Set: Used later to evaluate the trained model's performance on unseen data.
A common split is 80% training and 20% testing.

4. **CNN Training**

The Convolutional Neural Network (CNN) is trained using the training dataset.

The model learns patterns and features from the topography images through multiple convolutional layers, activation functions, pooling layers, and fully connected layers.
Training continues for multiple iterations (epochs) until an optimal performance is reached.

5. Accuracy Evaluation

Once training is complete, the system checks whether the accuracy of the model is acceptable. The accuracy threshold is pre-defined (e.g., 90%).

6. Decision: Accuracy Accepted?

If No, the model goes back for re-training with adjusted parameters (e.g., learning rate, batch size, augmentation). If Yes, the model proceeds to the testing phase.

7. Apply Test Set to Neural Network

The trained CNN model is evaluated using the test dataset to validate its generalization ability.
The model predicts labels for the test images, and performance metrics such as accuracy, precision, recall, and F1-score are calculated.

8. Computer Accuracy

The model's final accuracy is computed, and the results are analyzed. If the accuracy meets expectations, the process is complete.

9. Stop

The training and evaluation process end, and the final trained model is ready for deployment.

10. Output

The result of this analysis determines whether the given medical image is cancerous or non- cancerous.

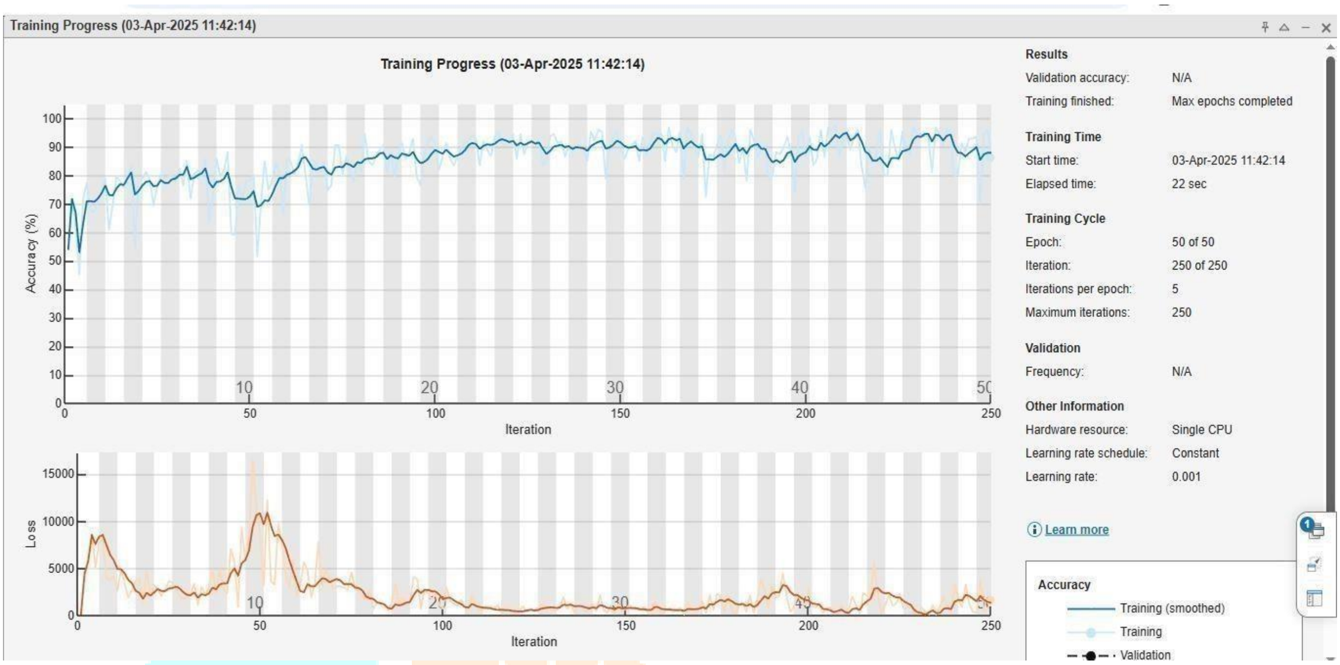
Conclusion

This flowchart represents an iterative process for CNN training and validation. If accuracy is not satisfactory, the system re-trains the model, improving its performance until it meets the required threshold. Once finalized, the model is evaluated using test data, and its accuracy is computed before concluding the process.

V. RESULTS AND DISCUSSION

The work was tested on MRI images of bone cancer patients in both existing and proposed methods. In existing methods use ANN Classifier and in proposed method use CNN Classifier.
The corresponding results shown in below figure.

Training progress (Accuracy, Loss):



a) **Accuracy Graph (Top)**

The y-axis represents the accuracy (%) of the model. The x-axis represents the iteration count.

The blue line shows how training accuracy improves as iterations progress.

Initially, accuracy fluctuates significantly but stabilizes around 90% as training nears completion. The lighter blue line represents raw training accuracy, while the darker line is a smoothed version.

b) **Loss Graph (Bottom)**

The y-axis represents the loss value.

The x-axis represents the iteration count.

The brown line indicates how loss decreases over time.

Initially, the loss is very high, but it reduces significantly as training progresses, which is a good sign of learning. Some fluctuations in loss can be seen mid-training, but overall, it trends downward, indicating proper convergence.

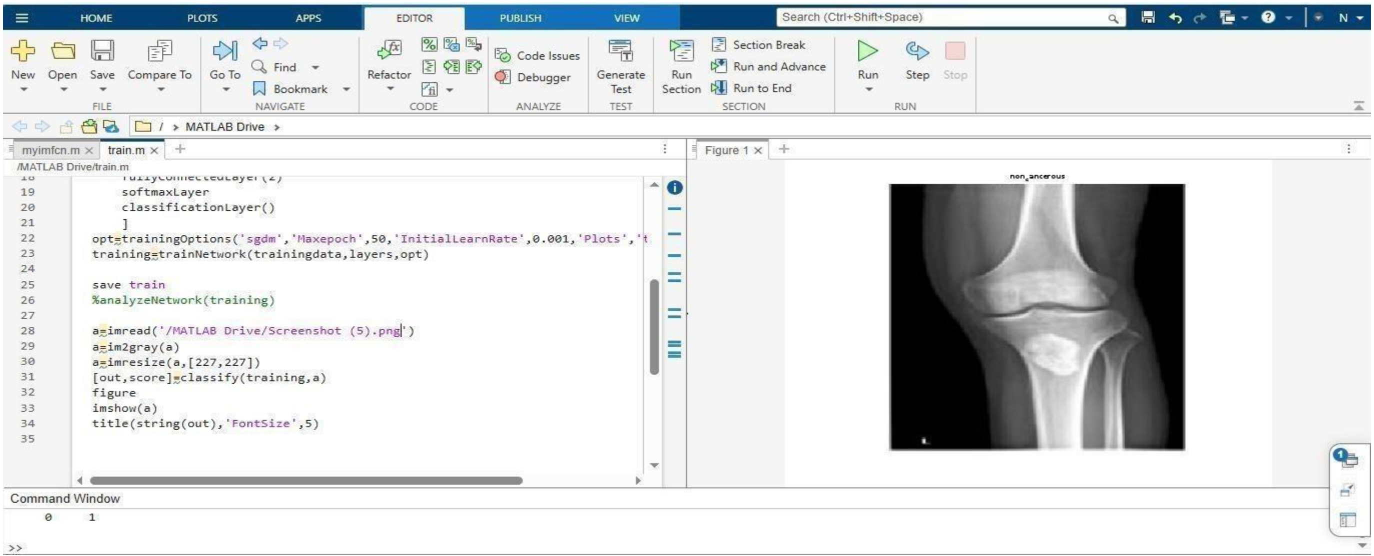


Fig: Output from input image

The above image shows a MATLAB-based CNN model for bone cancer detection. The script trains a CNN, processes an X-ray image, classifies it, and displays the result. It uses deep learning layers and an optimizer to predict whether the bone is cancerous or not.

The below image shows confusion matrix helps evaluate the performance of the CNN model in terms of correct predictions (True Positives and True Negatives) and misclassifications (False Positives and False Negatives). By analyzing the matrix, you can gain insights into how well the model is classifying bone cancer images and whether it is prone to errors such as misclassifying malignant cases as benign (False Negatives) or benign cases as malignant (False Positives).

Fig: Confusion Matrix for test data split

By this matrix we can calculate the Accuracy, Precision, FPR, TPR by the values obtained at the places of True Positives and True Negatives, False Positives and False Negatives

The CNN model was trained with augmented medical images and achieved the following metrics:

- Accuracy: 81.8%
- Precision: 82.5%
- Recall: 78.6%
- False Positive Rate (FPR): 15.2%

Compared to an ANN model (accuracy: 72.07%), the CNN outperforms significantly, especially in detecting small and complex tumor region.

Conclusion

The implementation of Bone Cancer Detection in MATLAB using Convolutional Neural Networks (CNNs) presents a significant advancement in medical imaging and diagnostics. This project successfully automates the detection and classification of bone cancer, reducing human error and improving diagnostic efficiency. The CNN-based classification and segmentation approach enhances the accuracy of detecting cancerous regions, leveraging the detailed structural information provided by CT images. This automated system not only accelerates diagnosis but also supports healthcare professionals by providing a reliable, scalable, and efficient tool for early cancer detection.

Future Scope

The proposed method can be improved to recognize and forecast cancer stage in various images such as CT, X- Ray, and MRI. It could be enhanced to be more accurate in predicting phases. The approach can be extended to implement in smart phones or cloud computing, with the advantages of decreased computational burden, cheap cost, and very few parameters to setup.

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