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Bone Cancer Detection and Classification Using Owl Search Algorithm with Deep Learning on X-Ray Images

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Abstract: Bone cancer is treated as a serious wellbeing issue, and, in numerous cases, it causes quiet passing. Early location of bone cancer is effective in lessening the spread of dangerous cells and diminishing mortality. Since the manual location handle could be a difficult errand, it is required to plan an mechanized framework to classify and recognize the cancerous bone and the sound bone. Hence, this article creates an Owl Look Calculation with a Profound Learning-Driven Bone Cancer Discovery and Classification (OSADL-BCDC) strategy. The OSADL-BCDC calculation takes after the rule of exchange learning with a hyperparameter tuning procedure for bone cancer discovery. The OSADL-BCDC show utilizes Initiation v3 as a pretrained show for the include extraction prepare which does not require a manual division of X-ray pictures. Other than, the OSA is connected as a hyperparameter optimizer for upgrading the viability of the Beginning v3 strategy. At long last, the long short-term memory (LSTM) approach is utilized for recognizing the nearness of bone cancer. The proposed OSADL-BCDC strategy decreases conclusion time and accomplishes speedier joining. The exploratory analysis of the OSADL-BCDC calculation is tried employing a set of restorative pictures and the results were measured beneath distinctive viewpoints. The comparison consider highlighted the progressed execution of the OSADL-BCDC demonstrate over existing calculations.

INDEX TERMS: Medical imaging; Bone cancer; Deep learning; Artificial intelligence; Owl search algorithm

1. INTRODUCTION

To develop an efficient system for bone cancer detection and classification using the Owl Search Algorithm for feature optimization and deep learning techniques on X-ray images

1.2 Objective

1. To preprocess and enhance X-ray images for better analysis of bone structures.
2. To apply the Owl Search Algorithm to optimize feature selection, ensuring accuracy and computational efficiency.
3. To design and train a deep learning model for detecting and classifying bone cancer into benign and malignant categories.
4. To evaluate the system's performance using metrics like accuracy, precision, recall, and F1-score.

Bone cancer is a serious and life-threatening condition characterized by the uncontrolled growth of abnormal cells within the bone. It can be classified into benign and malignant tumors, with malignant tumors being more aggressive and potentially fatal. Early detection and accurate classification are crucial for effective treatment and prognosis. Traditional diagnostic approaches depend on manual analysis by radiologists, which is not only time-consuming but also prone to human error. This underscores the need for automated systems that can assist medical professionals in making faster and more precise diagnoses.

The human body comprises 206 bones, which play an essential role in movement and support. Bone ligaments, composed of fibrous tissues and spongy bone marrow, contribute to overall skeletal function. In recent years, there has been a significant increase in the incidence of bone cancer, particularly malignant cases. Although benign bone tumors are more prevalent, malignant bone cancer poses a greater threat due to its aggressive nature and lower survival rates. According to statistics, approximately 3,500 individuals in the U.S. were diagnosed with bone cancer in 2018, with nearly 47% of cases resulting in mortality. This highlights the urgent need for improved diagnostic techniques to enhance patient outcomes.

Early and accurate prognosis is a key factor in improving survival rates among bone cancer patients. Bone tumors arise from healthy cells that undergo malignant transformation, eventually spreading to other parts of the body. This progression weakens the affected bones, leading to structural damage and increased fracture risk. The severity of bone cancer is assessed based on its grade and stage, which determine its growth rate and potential for metastasis. Physicians primarily rely on X-ray imaging to diagnose bone tumors, as the differences in X-ray absorption between cancerous and healthy bones create distinguishable patterns. However, manual tumor detection requires significant expertise and can be error-prone.

The advent of artificial intelligence (AI) and deep learning (DL) has revolutionized various medical applications, including disease detection and classification. Deep learning models, such as convolutional neural networks (CNNs), have demonstrated exceptional performance in analyzing medical images and identifying complex patterns. These models are capable of processing two-dimensional medical images with an accuracy comparable to that of human experts. Researchers have successfully employed AI techniques for diagnosing diseases using MRI, radiography, microscopy, ultrasound, and endoscopy. Similarly, AI-based methods can be effectively applied to detect bone cancer from plain radiographs, reducing the reliance on manual interpretation.

To further enhance the accuracy and efficiency of bone cancer detection, this project integrates the Owl Search Algorithm (OSA) for feature optimization with deep learning models for automated classification. The proposed Owl Search Algorithm with a Deep Learning-Driven Bone Cancer Detection and Classification (OSADL-BCDC) method utilizes Inception v3 as a pretrained model for feature extraction. Unlike traditional approaches, this method eliminates the need for manual segmentation of X-ray images. Additionally, OSA optimizes the hyperparameters of the deep learning model, improving its performance. The final classification of bone tumors is performed using the long short-term memory (LSTM) technique, ensuring high precision and reliability.

By leveraging advanced AI techniques and metaheuristic optimization, the OSADL-BCDC model aims to provide a robust and efficient solution for bone cancer detection and classification. The integration of deep learning and optimization algorithms reduces human errors, accelerates diagnosis, and enhances patient care. This novel approach represents a significant advancement in medical imaging and has the potential to transform the way bone cancer is diagnosed and treated. The experimental evaluation of the OSADL-BCDC algorithm demonstrates its effectiveness in improving diagnostic accuracy and efficiency, offering a promising solution for the early detection of bone cancer.

II. LITERATURE SURVEY

Ratley, A., Minj, J., and Patre, P. (2020) conducted a comprehensive review on leukemia disease detection and classification using machine learning approaches. The study highlights how leukemia, characterized by an abnormal increase in white blood cells in the bone marrow, is classified into acute and chronic types, further subdivided into lymphocytic and myeloid categories. The paper reviews various image processing and machine learning techniques for leukemia detection, emphasizing their strengths and weaknesses. The findings provide valuable insights into existing methodologies, which can aid researchers in selecting appropriate techniques for future studies. [1]

Nadeem, M.W., et al. (2020) explored the application of deep learning in bone age assessment, emphasizing its significant impact on medical image analysis and pattern recognition. The study reviews a wide range of deep learning models applied for segmentation, prediction, and classification in bone age assessment. The paper also discusses emerging trends in deep learning, challenges faced in implementing these models, and future research directions. By analyzing numerous scientific publications, the study provides a critical evaluation of deep learning techniques and their potential in transforming medical diagnostics. [2]

Shrivastava, D., et al. (2020) investigated the role of machine learning techniques in detecting bone cancer. The study emphasizes the importance of early detection in improving patient survival rates and elaborates on various classification techniques used for identifying tumors. Using bone CT scan datasets in DICOM format, the study demonstrates how machine learning models enhance the accuracy of medical diagnoses. The results indicate significant improvements in bone cancer classification, proving that machine learning can be an effective tool in medical imaging analysis. [3]

Arunachalam, H.B., et al. (2019) developed an automated system for assessing viable and necrotic tumors in osteosarcoma using machine learning and deep learning models. The study employed 40 digitized whole slide images to train 13 machine-learning models and a deep-learning architecture, with a Support Vector Machine (SVM) yielding the best results. The research further developed a tumor-prediction map to visualize viable and necrotic tumor regions. The proposed automated assessment system lays the foundation for more precise and efficient tumor detection, which can be extended to other types of tumors. [4]

Eweje, F.R., et al. (2021) developed a deep learning algorithm for classifying bone lesions using routine MRI scans. The study addresses the challenge radiologists face in differentiating benign from malignant bone lesions due to their similar imaging appearances. By incorporating patient demographics and MRI scans, the deep learning model improves classification accuracy. The research demonstrates the potential of AI-driven solutions in enhancing radiological diagnostics, thereby reducing diagnostic errors and improving patient outcomes. [5]

He, Y., et al. (2020) proposed an AI-based model for classifying primary bone tumors in the proximal femur using plain radiographs. The study involved training a convolutional neural network (CNN) model on 538 femoral images, categorizing them as benign, malignant, or no tumor. The model's performance was evaluated using fivefold cross-validation and compared with human doctors. The findings suggest that CNN-based approaches can achieve high accuracy in tumor classification, potentially assisting clinicians in making more informed decisions.[6]

vonSchacky, C.E., et al. (2021) developed a multitask deep learning model for the segmentation and classification of primary bone tumors on radiographs. The study analyzed radiographs from 934 patients, implementing a deep learning model that simultaneously performed bounding box placement, segmentation, and classification. The model achieved an accuracy of 80.2%, outperforming radiology residents and matching the performance of musculoskeletal radiologists. The research underscores the potential of AI in automating tumor detection and classification, significantly aiding radiologists in diagnostic workflows. [7]

III. PROPOSED METHOD

3.1 Pre-Processing

To enhance the dataset and address constraints and imbalance issues, data augmentation techniques such as **rotation (90° clockwise)** and **zooming (factors 0.5 and 0.8)** are applied. These augmentations introduce variability in the dataset, improving generalization and robustness.For image refinement, **Gaussian filtering** is employed to reduce noise, preserving essential features while eliminating unwanted distortions.

3.2 Feature Extraction

Inception v3, a pretrained Convolutional Neural Network (CNN), is used for efficient feature extraction. The model includes convolutional, pooling, and fully connected layers, ensuring optimal feature mapping and classification.Inception v3 enhances adaptability and reduces computational complexity by utilizing optimized convolutional kernels, making it suitable for deep learning applications in medical imaging.

3.3 Optimization with Owl Search Algorithm (OSA)

OSA optimizes hyperparameters of the Inception v3 architecture. The algorithm models **owls as agents** navigating a multi-dimensional search space to minimize the objective function, leading to improved classification performance.

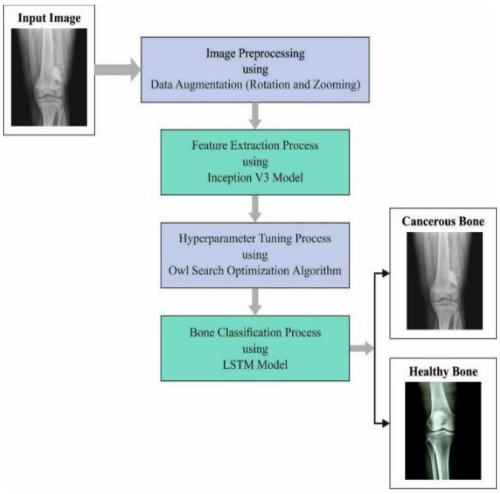

Fig 1. Working Process of OSADL-BCDC Method

OSA provides key benefits:

- **Feature Selection**: Extracts the most relevant features, reducing model complexity.
- **Hyperparameter Tuning**: Optimizes learning rate, number of layers, and activation functions to enhance accuracy.
- **Exploration and Exploitation**: Balances global and local search strategies to prevent overfitting.
- **Convergence Speed**: Accelerates training and testing for rapid diagnosis.

3.4 Classification

A Long Short-Term Memory (LSTM) network classifies X-ray images as cancerous or normal. The LSTM architecture employs gate mechanisms (**forget, input, and output gates**) to manage long-term dependencies, retaining only the most relevant information for classification.

3.5 Softmax Activation

The **Softmax function** is applied to assign confidence scores to the classified results, ensuring better interpretability and decision-making.

3.6 Advantages of the Proposed Method

- **Eliminates Manual Segmentation**: Automates feature extraction, reducing time and effort.
- **Enhances Feature Extraction**: Leverages transfer learning with Inception v3.
- **Optimizes Model Performance**: Utilizes OSA for efficient hyperparameter tuning.
- **Achieves Faster Convergence**: Reduces overall diagnosis time.
- **Outperforms Existing Algorithms**: Provides higher accuracy and efficiency, as demonstrated in experimental evaluations.

Step-by-Step Execution of OSA

1. **Initialize Population**: Generate multiple owl agents with random hyperparameter values.
2. **Fitness Evaluation**: Assess each owl's performance using a cost function based on classification accuracy.
3. **Update Positions**: Modify owl positions by imitating hunting behavior to explore the solution space.
4. **Selection Process**: Retain the best solutions and discard weaker ones to refine hyperparameter choices.
5. **Convergence Check**: Repeat iterations until optimal values are identified or stopping criteria are met.
6. **Apply Optimized Parameters**: Use the best-selected parameters to train the **Inception v3 + LSTM model**.
7. **Final Classification**: Classify X-ray images as **cancerous or non-cancerous** using the optimized model predictions.

IV RESULT

The proposed model is simulated using Python 3.6.5 tool on PC i5-8600k, GeForce 1050Ti 4GB, 16GB RAM, 250GB SSD, and 1TB HDD. The parameter settings are given as follows: learning rate: 0.01, dropout: 0.5, batch size: 5, epoch count: 50, and activation: ReLU. The performance analysis of the OSADL-BCDC algorithm is tested using a set of X-ray images gathered from various sources like The TCIA (Cancer Imaging Archive), and the Indian Institute of Engineering Science and Technology, Shibpur (IIEST). In this study, a set of 200 images is taken with 100 images under the cancerous class and 100 images under the healthy classes.

Fig 2: Sample images

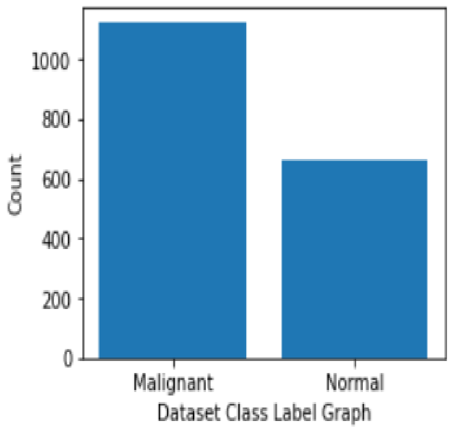

Fig 3: Dataset Class Label Graph

The graph shows that the "Malignant" category has a count of approximately 1050, while the "Normal" category has a count of around 580. This indicates an imbalance in the dataset, with a significantly higher number of data points classified as "Malignant" compared to “Normal.

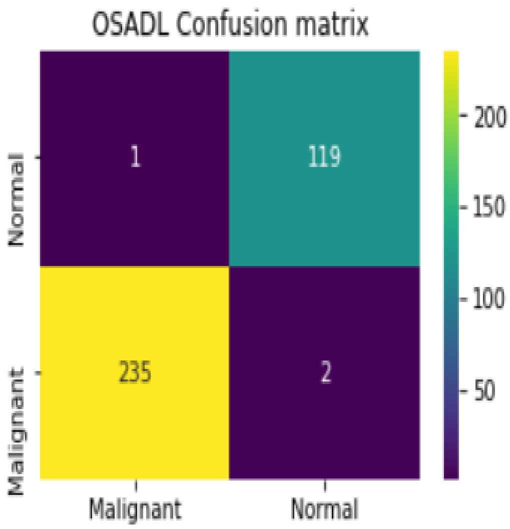

Fig 4: Confusion Matrices of OSADL-BCDC Method

The confusion matrices created by the OSADL-BCDC algorithm under dissimilar epochs. With 500 epochs, the OSADL-BCDC technique has detected 235 instances in the cancerous class and 119 instances in the healthy class.

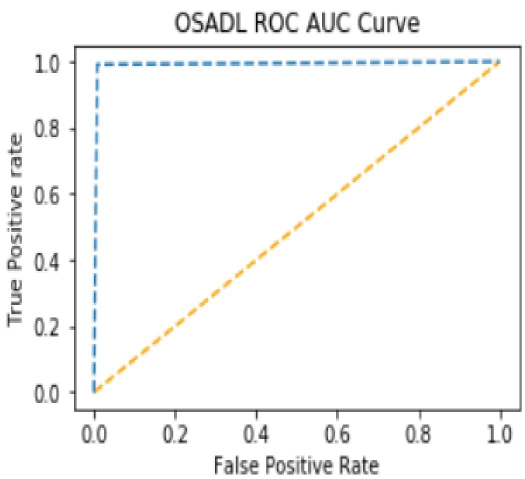

Fig 5: OSADL ROC AUC Curve

The provided image depicts an OSADL ROC AUC (Receiver Operating Characteristic Area Under the Curve) curve, a graphical representation of the performance of a binary classification model. The True Positive Rate (sensitivity) is plotted against the False Positive Rate (1-specificity). The blue dashed line represents the performance of the model, while the yellow dashed line represents random chance. The AUC value, which is the area under the ROC curve, quantifies the overall performance of the model, with a higher AUC indicating better performance.

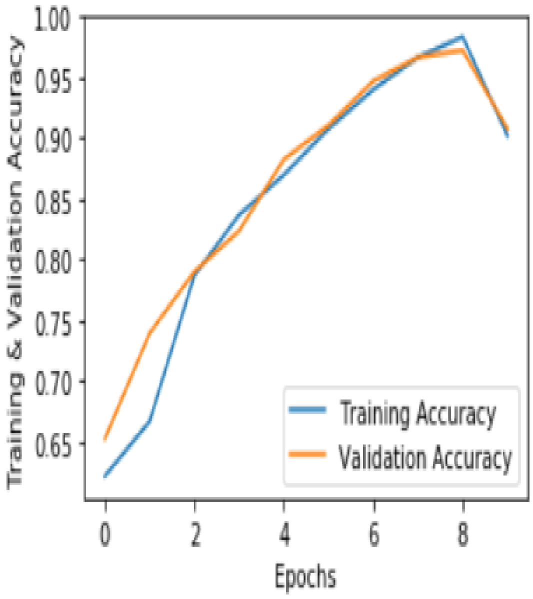

Fig 6: Training and validation accuracy

The provided graph illustrates the training and validation accuracy of a model over 10 epochs. Initially, both accuracies increase, peaking around epoch 8, before the validation accuracy declines, suggesting potential overfitting. The model achieves a peak accuracy of approximately 95%.

V. CONCLUSION

The OSADL-BCDC method effectively identifies and classifies bone cancer using X-ray images by leveraging data augmentation, feature extraction with OSA-optimized Inception v3, and classification through an LSTM network. The model eliminates the need for manual segmentation, significantly reducing diagnosis time and enhancing accuracy, achieving a maximum of 95%. Experimental evaluations demonstrate its superior performance over existing methods. Future research can explore deep instance segmentation, explainable AI for clinical trust, and multimodal imaging integration to provide a more comprehensive bone cancer diagnosis.

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