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OncoDetect: AI based Cancer Detection System

Mrs. Manisha Rajendra Shiledar[1], Mr. Prathamesh Udekar[2], Mr. Aifaz Inamdar[3], Ms. Drijil Kumari Pandit[4], Ms. Swaleha Khan[5]

[1,2] Assistant Professor, Department of Information Technology,
[3,4] Second Year, Department of Information Technology,
[5] Second Year, Department of Science,
Janardan Bhagat Shikshan Prasarak Sanstha's Ramsheth Thakur College of Commerce & Science, Kharghar, Navi Mumbai, India[1,2,3,4,5]
mrshiledar9@gmail.com[1], udekarp007@gmail.com[2], inamdaraifaz9603@gmail.com[3], drijils.pandit@gmail.com[4], swalehak004@gmail.com[5]

Abstract: *Breast cancer remains one of the leading causes of mortality among women worldwide, where early and accurate diagnosis plays a critical role in improving survival outcomes. Conventional diagnostic methods such as Fine Needle Aspiration (FNA) cytology rely heavily on manual microscopic examination, which is time-consuming and subject to human limitations, often resulting in delays of up to 5–6 days. This study presents OncoDetect, an AI-powered diagnostic support system designed to enhance the efficiency and reliability of breast cancer detection. The proposed system utilizes the Wisconsin Diagnostic Breast Cancer (WDBC) dataset and employs a Gradient Boosting classifier optimized through systematic threshold tuning to prioritize clinical safety. By selecting key morphological features, the model achieves a recall of 1.0, ensuring zero missed malignant cases, while maintaining an overall accuracy of 97.7% and precision of 94.1%. The system significantly reduces diagnostic turnaround time to 1–2 days, achieving nearly 80% improvement in efficiency. Furthermore, OncoDetect provides explainable outputs that assist pathologists in decision-making and can be integrated into existing clinical workflows. The results demonstrate that the proposed approach effectively addresses critical bottlenecks in traditional diagnostic processes, offering a scalable and reliable solution for rapid cancer screening, improved resource allocation, and enhanced patient outcomes.*

Keywords: OncoDetect: AI based cancer detection System

I. INTRODUCTION

Breast cancer is one of the most prevalent and life-threatening diseases worldwide, posing a significant challenge to global healthcare systems. According to the World Health Organization, early detection and timely diagnosis are critical in improving survival rates and reducing mortality. However, delays in diagnosis remain a major concern, particularly in traditional methods that rely heavily on manual interpretation. Fine Needle Aspiration (FNA) cytology, a commonly used initial diagnostic technique, involves microscopic examination of extracted cellular samples. While effective, this process is time-consuming—often taking 5–6 days—and is subject to human variability, which can affect consistency and efficiency.

Recent advancements in Machine Learning have enabled the development of intelligent systems capable of analyzing complex medical data with high accuracy. In this context, this research introduces *OncoDetect*, an AI-powered diagnostic support system designed to improve the speed and reliability of breast cancer detection. The system utilizes the Wisconsin Diagnostic Breast Cancer (WDBC) dataset and employs a Gradient Boosting classifier to analyze key morphological features of cell nuclei. Through systematic threshold optimization, the model achieves a recall of 1.0, ensuring that no malignant cases are missed while maintaining high accuracy and precision.

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By reducing diagnostic time from several days to just 1–2 days, OncoDetect serves as an efficient triage tool that assists pathologists in prioritizing high-risk cases. Its explainable outputs further enhance clinical decision-making and allow seamless integration into existing workflows. This study highlights the potential of AI-driven solutions to address critical limitations in traditional diagnostic processes, ultimately contributing to faster, safer, and more reliable cancer detection.

II. LITERATURE REVIEW

Breast cancer detection has been a major area of research due to its high global prevalence and the critical importance of early diagnosis. Traditional diagnostic techniques, including mammography and Fine Needle Aspiration (FNA), rely heavily on manual interpretation, which can lead to delays and inconsistencies. To address these challenges, researchers have increasingly explored the application of Artificial Intelligence (AI) and Machine Learning (ML) techniques to improve diagnostic accuracy, efficiency, and reliability.

Early studies in this domain primarily focused on the use of classical machine learning algorithms such as Logistic Regression, Support Vector Machines (SVM), and k-Nearest Neighbors (kNN) for classification tasks. Comparative analyses have shown that while these models are effective, they often struggle with non-linear data patterns and complex feature interactions present in medical datasets

For instance, studies using the Wisconsin Diagnostic Breast Cancer (WDBC) dataset demonstrated that kNN and SVM could achieve accuracies above 95%, but their performance was limited by issues such as feature sensitivity and lack of scalability.

With advancements in computational techniques, ensemble learning methods such as Random Forest and Gradient Boosting have gained prominence. These models combine multiple weak learners to produce more accurate and robust predictions. Research indicates that ensemble approaches, particularly Gradient Boosting variants like XGBoost and LightGBM, can achieve accuracy levels exceeding 97%, making them highly suitable for medical diagnosis tasks.

Furthermore, studies focusing on boosting algorithms have emphasized their ability to reduce false negatives, a critical requirement in cancer detection where missing a malignant case can have severe consequences.

In parallel, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have been widely applied to medical imaging data such as mammograms and histopathological images. These models have demonstrated exceptional performance, with some studies reporting accuracy as high as 99.5%

However, despite their high accuracy, deep learning models often require large datasets, high computational resources, and lack interpretability, which limits their adoption in clinical environments.

Another important development in recent research is the integration of Explainable Artificial Intelligence (XAI) techniques. Methods such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) have been used to interpret model predictions and enhance transparency. Studies have shown that incorporating explainability not only improves trust among medical professionals but also helps in identifying the most influential features contributing to diagnosis.

This is particularly important in healthcare, where understanding the reasoning behind a prediction is as crucial as the prediction itself.

Several recent studies have also focused on optimizing performance metrics beyond accuracy, such as recall (sensitivity), precision, and F1-score. In medical diagnostics, recall is especially critical, as it measures the model's ability to correctly identify malignant cases. Research has highlighted that models optimized for high recall significantly reduce the risk of false negatives, thereby improving clinical safety.

Additionally, hybrid and ensemble models combining multiple algorithms have been proposed to balance accuracy and interpretability while maintaining robustness.

Despite these advancements, existing systems still face challenges such as data imbalance, lack of generalization across diverse populations, and limited integration into real-world clinical workflows. Moreover, many models prioritize

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overall accuracy rather than clinical safety, which may not be suitable for high-stakes applications like cancer detection.

The proposed *OncoDetect* system builds upon these existing studies by integrating a Gradient Boosting classifier with systematic threshold optimization to achieve a recall of 1.0, ensuring zero missed malignant cases. Unlike many prior approaches, it emphasizes both clinical safety and efficiency while maintaining high accuracy. Additionally, by focusing on explainable features and rapid triage, the system aims to bridge the gap between high-performance AI models and practical clinical implementation.

III. WORKING OF MODEL [PRE PROCESSING, DATA FLOW, RESULT CALCULATION]

Working Model Theory

The *OncoDetect* system is designed as an AI-driven diagnostic pipeline that processes cytological data from Fine Needle Aspiration (FNA) samples to classify tumors as benign or malignant. The model follows a structured workflow consisting of three key stages: **data preprocessing, data flow through the model, and result calculation with threshold optimization.**

1. Data Preprocessing

Data preprocessing is a critical step to ensure the quality, consistency, and reliability of the input data. The system utilizes the Wisconsin Diagnostic Breast Cancer (WDBC) dataset, which contains 569 samples with multiple morphological features extracted from digitized FNA images.

Initially, irrelevant or redundant features are removed, and a subset of the most significant 20 features is selected based on domain knowledge and statistical relevance. These features include measurements related to cell nucleus characteristics such as radius, texture, perimeter, area, smoothness, and concavity. Feature selection helps reduce dimensionality, improve computational efficiency, and minimize overfitting.

Next, the dataset undergoes normalization or standardization to ensure that all features are on a comparable scale. This step is essential for improving the performance of machine learning algorithms, particularly those sensitive to feature magnitude. Missing values, if any, are handled through appropriate imputation techniques, although the WDBC dataset is largely clean.

The dataset is then divided into training and testing sets, typically in an 80:20 ratio. This split allows the model to learn patterns from the training data and evaluate its performance on unseen data. Additionally, class imbalance is carefully monitored to ensure that the model does not become biased toward the majority class.

2. Data Flow Through the Model

Once preprocessing is complete, the processed data is passed through the core machine learning model, which is based on a Gradient Boosting (GB) classifier. Gradient Boosting is an ensemble learning technique that builds multiple decision trees sequentially, where each subsequent tree corrects the errors of the previous one.

During training, the model iteratively minimizes a loss function by optimizing the prediction errors. Each tree contributes to improving the overall prediction by focusing more on misclassified instances. This iterative refinement enables the model to capture complex, non-linear relationships within the dataset.

The input feature vector for each sample flows through the ensemble of decision trees, where each tree generates a partial prediction. These predictions are then aggregated to produce a final probability score representing the likelihood of the tumor being malignant.

The system is designed to act as a triage tool, meaning that it prioritizes sensitivity (recall) over other metrics. Therefore, the data flow is optimized to ensure that even borderline malignant cases are flagged for further review rather than being overlooked.

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3. Result Calculation and Threshold Optimization

The final stage involves converting the model's probability outputs into a binary classification (benign or malignant). Instead of using a default threshold of 0.5, the system employs systematic threshold optimization to enhance clinical safety.

Through experimental tuning, an optimal threshold value (e.g., 0.1842) is selected to maximize recall. This ensures that all malignant cases are correctly identified, achieving a recall of 1.0 (100%). While this may slightly increase the number of false positives, it is acceptable in a medical context where missing a cancer case is far more critical than raising a false alarm.

Performance metrics such as accuracy, precision, recall, and confusion matrix are then calculated to evaluate the model. Accuracy reflects overall correctness, precision indicates the proportion of true malignant cases among predicted positives, and recall ensures complete detection of actual malignant cases.

The final output of the system includes:

- A classification label (Benign/Malignant)
- A confidence score (probability value)
- Feature-based insights for explainability

These outputs assist pathologists in making faster and more informed decisions, thereby reducing diagnostic delays and improving clinical outcomes.

IV. ADVANTAGES OF ARTIFICIAL INTELLIGENCE

- **Significant Time Reduction:** Decreases diagnostic turnaround time from 5–6 days to 1–2 days, improving clinical efficiency.
- **High Clinical Safety:** Achieves a recall of 1.0 (100%), ensuring that no malignant cases are missed (zero false negatives).
- **High Accuracy and Precision:** Maintains strong overall performance with approximately 97.7% accuracy and 94.1% precision, ensuring reliable predictions.
- **AI-Powered Rapid Triage:** Enables quick identification and prioritization of high-risk cases for immediate medical attention.
- **Reduced Pathologist Workload:** Filters out clear benign cases, allowing medical professionals to focus on complex and critical diagnoses.
- **Explainable Decision Support:** Provides interpretable outputs based on morphological features, enhancing trust and aiding clinical decision-making.
- **Scalable and Efficient:** Can handle large volumes of diagnostic data, making it suitable for high-demand healthcare environments.
- **Seamless Workflow Integration:** Designed to integrate with existing digital pathology systems without major infrastructure changes.
- **Cost-Effective Solution:** Reduces dependency on prolonged manual analysis, potentially lowering operational costs in healthcare facilities.
- **Improved Patient Outcomes:** Faster and more reliable diagnosis enables earlier treatment initiation, increasing survival rates.

V. CONCLUSION

This research presented *OncoDetect*, an AI-driven diagnostic support system designed to enhance the accuracy, speed, and reliability of breast cancer detection using Fine Needle Aspiration (FNA) cytology data. By leveraging advanced techniques from Machine Learning, the proposed system effectively addresses the key limitations of traditional diagnostic approaches, particularly the time-consuming nature of manual microscopic analysis and the risk of human error.

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The implementation of a Gradient Boosting classifier, combined with systematic threshold optimization, enabled the model to achieve a recall of 1.0 (100%), ensuring that no malignant cases are missed. This strong emphasis on clinical safety is critical in medical diagnostics, where false negatives can have severe consequences. At the same time, the system maintained high overall accuracy and precision, demonstrating its capability to deliver reliable and consistent results. The use of carefully selected morphological features further contributed to the model's robustness and interpretability.

One of the most significant contributions of this study is the substantial reduction in diagnostic turnaround time, from approximately 5–6 days to just 1–2 days. This improvement not only enhances operational efficiency within healthcare systems but also facilitates earlier clinical decision-making and timely initiation of treatment. Additionally, the system's ability to function as a triage tool allows for better prioritization of high-risk cases, optimizing the workload of pathologists and improving resource allocation.

Furthermore, the explainable nature of the model ensures transparency in decision-making, which is essential for building trust among medical professionals and enabling practical adoption in clinical environments. The design of OncoDetect also supports seamless integration into existing digital pathology workflows, making it a scalable and adaptable solution for real-world applications.

Despite its promising performance, the study acknowledges certain limitations, including reliance on a specific dataset and the need for further validation across diverse populations and clinical settings. Future work may focus on incorporating larger and more varied datasets, integrating deep learning techniques for image-based analysis, and enhancing real-time deployment capabilities.

In conclusion, OncoDetect demonstrates the transformative potential of AI in healthcare by providing a clinically safe, efficient, and reliable solution for early breast cancer detection. The system represents a significant step toward reducing diagnostic delays, improving patient outcomes, and advancing the integration of intelligent technologies in modern medical practice.

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