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Comparative Review of Mammary Cancer using Machine Learning Techniques

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***Abstract*— The discovery of mammary cancer primarily depends on examining tissues slide through a microscope. This method is time consuming and subjects to human error. Various traditional machine learning techniques require specialists to manually select features such as texture, color or shapes. These aspects frequently don't work well for every image, especially when the slides have different hues or staining methods. This paper presents an automated system that employs on Convolutional Neural Networks (CNN) for the analysis of mammary cancer. This study is to develop a patch-based CNN framework capable of automatically analyze small parts of large breast tissue images and helps to identify whether they are benign or malignant. Now, instead of depending on manually selected features, system learns important patterns directly from the image patches. An accurate final diagnosis for the entire slide or patient is subsequently created by combining these patch-level findings. In order to demonstrate how much better and more dependable CNN is, the study also contrasts its performance with that of conventional techniques.**

***Keywords*— Mammary Cancer Detection, Convolutional Neural Networks (CNN), Patch Based Classification, Histopathology Image Analysis, Automated Diagnosis.**

I. INTRODUCTION

The World Health Organization says that breast cancer causes many deaths among women, so finding it early and diagnosing it correctly is more important than ever. Discovering cancer early not only saves lives but also lets doctors plan treatments that lower the chance of it coming back and improve overall well-being. Although doctors regularly use imaging tests like mammograms, ultrasounds, and MRIs to screen and assess risk, the best way to confirm cancer is still to look at biopsy samples under a microscope after staining them with hematoxylin and eosin (H&E).

A. Challenges in Manual Histopathological Analysis

The evaluation of whole-slide images (WSIs) requires more efforts, much time, and can produce different outcomes from different observers perspectives. Every WSI consist of millions of pixels, containing large areas of normal tissues, which may lead to difficulties in examinations.

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These challenges comes during identification of aggressive or mixed tumors, which may lead to showing of slight differences in cell arrangement and structure of the tissues. Such complexities comes during urgent need for machinery elements during diagnosis that can aid doctors in achieving greater accuracy and effectiveness.

B. Categories of Breast Cancer

Identifying different kinds of breast cancer is very essential for correct clinical evaluation. This also helps to create automated detection tools. Breast cancer is divided into two main categories: non-invasive ("in situ") and invasive, which is based on how cells have branched the membrane of lobules or ducts.

Non-invasive (In Situ) Carcinomas:

Ductal carcinoma in situ (DCIS): is a form of breast cancer which remains within the milk ducts. It is normally detected accidentally by doctors during routine screening mammograms before a woman develops any symptoms [5]. Lobular Carcinoma in Situ (LCIS): LCIS is noticed by abnormal cell growth in the lobules which do not invade neighbouring tissues. It acts like an indication for the increased breast cancer risk instead of being differentiated as a correct cancer itself [6].

Invasive Breast Cancer

Most of the clinically identified breast cancers comes in the category of invasive cancer, showing historical differences that can affect various treatment options .

Invasive Ductal Carcinoma (IDC): IDC, sometimes known as invasive carcinoma consisting no specific type (NST), makes up 70–80% of invasive breast cancer cases. It arises from the ductal epithelium and spread into neighboring tissues [7].

Invasive Lobular Carcinoma (ILC): 10–15% of cases are reported due to ILC and begins in the lobules. Many a times, it affects neighboring areas in a single-file or loosen sheet manner, which is complicated in nature and difficult to detect through imaging methods. [8].

C. Significance of Histological Classification

Classification of tissues are necessary for assessing prognosis, forecasting clinical behavior and treatments. Various types of breast cancer like mucinous, tubular, and specific papillary carcinomas leads to better outcomes, while metaplastic and medullary

carcinomas are often more strong. Whereas, subtyping is based on histology aids in classification related to molecular differentiation. Therefore, accurate histopathological evaluation is important for individual breast cancer care.

D. Conventional Diagnostic Methods and Their Constraints

Traditional computer-aided diagnosis (CAD) methods rely on hand-crafted features such as texture descriptors, morphological attributes, nuclear segmentation, and graph-based tissue analysis to assist in automated cancer detection. These methods are quite sensitive to various variations in staining, tissue artifacts, and the accuracy of segmentation, which limits their robustness and reduces their applicability across various datasets and labs. Further, manual feature creation and preprocessing limit their scalability and reliability.

By merging histopathological knowledge with deep learning, contemporary diagnostic systems seek to enhance accuracy, speed, and consistency in the detection of breast cancer. These approaches provide the possibility of aiding pathologists in dealing with intricate and varied tumor types, ultimately improving patient results.

II. Literature Survey

Many studies and models were proposed to analyze breast cancer using medical images to improve issues like accuracy, expert dependency, false detection and many more. In a study, author combined deep learning models like Convolutional Neural Networks (CNN), Conditional Random Fields (CRF), and Structured Support Vector Machines (SSVM)to perform mass segmentation of medical images[1]. This study aimed at marking the exact shape and boundary of a tumor in the mammogram. However, their approach cannot handle Whole Slide Images(WSI)s. Alom et al. work showed advancement in segmentation medical images by using U-Net, Recurrent Residual U-Net(R2U-Net), recurrent convolution layer and residual block[2]. U-Net is used to segment medical images, it has encoder and decoder structure that captures both global as well fine details.R2U-net is an improved version with same parameter and recurrent residual extracts feature by processing same feature multiple times. This model was tested on retina vessles, skin and lungs lesions but not on breast cancer histopathology images. A patch-based CNN model was introduced by Spanhol et el.[3]. This model achieved higher accuracy but classified breast cancer on BreakHis dataset and there was no visualization feature.

Similarly, Cruz-Roa et al. proposed an automatic IDC detection system [4]. The system took whole slide images as input and used patch based three layer CNN layer that produced improved result as compared to the ML methods. However, this model had shallow architecture, had limitations due to patch selection and its dependence on experts provided annotation for training. Overall, all these approaches have played a crucial role in demonstrating the role of deep learning techniques in analysis of breast cancer, but they also have some unsolved issues like dependence on expert annotations, model insufficient for handling whole slide images, limited patch level processing. This indicates the need for improved system with better and efficient accuracy.

TABLE I. LITERATURE SURVEY

Author(s)	Work Title	Method Used	Key Contribution
Dhungel et al.	Segmentation of Mass in Mammograms	CNN, CRF, SSVM	Combination of DL with prediction from medical images.
Alom et al.	Recurrent Residual U-Net	U-Net, Recurrent Convolution, Residual block	Better segmentation for retina vessels, skin and lungs lesions
Spanhol et al.	Histopathological Image Classification	Patch-based CNN on BreaKHis dataset	Higher accuracy achieved
Cruz-Roa et al.	Automatic IDC detection in whole-slide image using CNN	Patch-based 3 layer CNN	Higher accuracy (84.23%) then traditional ML methods

A. Problem Statement

- None of the methods can handle the full whole slide image.
- Most of the model needed experts to label cancer regions.
- The models miss the larger picture because they focus on specific portions of the image rather than the entire slide.
- Training models such as CNN + CRF/SSVM and U-Net requires a lot of processing power.
- Doctors find it difficult to trust the models since they provide outcomes without providing an explanation.
- Models do not have visualization feature. Our model focuses on solving problem of incomplete and inaccurate detection of cancer due to large images sizes, loss of global data, dependency of small patches. It provides a complete deep learning based model that analyze the whole images, convert them into patches, extract meaningful patches and then finally classify cancerous region of those patches. And lastly aggregate the result of the patches to show accurate analysis if whole image slide.

III. PROPOSED METHODOLOGY

We aim to design a Deep Learning model that combines classification of cancerous tissue, feature extraction, and segmentation in order to create a complete diagnostic framework.

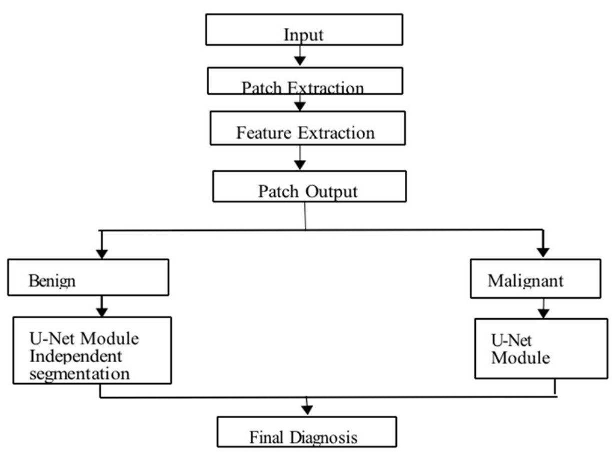

Fig. 1. Methodology

Input: The images that are fed to the system are Whole Slide Images (WSI), mammograms or histopathology slides. These input images go through some preprocessing steps like normalization, noise removal for quality enhancement of the images.

Patch Extraction: The Whole Slide Images(WSI) are very large in size and CNN is designed to handle images with smaller input dimensions. So WSI are broken into smaller and manageable patches that CNN can process easily and effectively.
Feature Extraction: Each Patches are then made to go through Deep Learning models like ResNet, DenseNet and EfficientNet to extract features like tissue texture, cell shapes, tumour boundary . these features help in easy detection of cancerous tissue. Patch Output: After extracting features successfully from each patch they are classified Benign (non -cancerous) or Malignant(cancerous). U-Net Module: In this independent segmentation is performed for better understanding. U-Net has a encoder and decoder structure that captures both global and fine details. MIL Aggregation: In this process all the individual patches results are combined or aggregated together to produce combined decision of a slide. If a patch is found to be cancerous whole slide is classified as cancerous. Final Diagnosis: Based on all the previous processes a complete output is provided for the whole slide. It determines whether cancer is present or not. The final output is reliable accurate as it is based on all previous process.

IV. RESULT

The comparison with various traditional machine-learning techniques that utilized handcrafted features such as texture, cell boundaries, and color distributions gave us the analysis that the classical models, attained average classification accuracies ranging from 72% to 83%, based upon the type of image and the quality of features. These models showed low performance when the images had variations in staining, illumination, and noise, highlighting their dependency on manually crafted features.
In contrast, the CNN-based system is proposed to attain higher accuracy by filling the gaps in the previous work. The patch based prediction along with MIL and U-NET Segmentation boosts the accuracy.

TABLE II. COMPARISON ANALYSIS

Work Title	Method Used	Parameters	Accuracy
Segmentation of Mass in Mammograms	CNN, CRF, SSVM	Structured Prediction, Graph Cuts, Patch-based Segmentation.	Dice Score: ≈ 90–91% Accuracy: ≈ 90%+
Recurrent Residual U-Net	U-Net, Recurrent Convolution, Residual block	Encoder-Decoder, Recurrent Convolution, Residual Blocks, Skip Connections	Dice Score: 82–84% Pixel Accuracy: ≈ 95%
Histopathological Image Classification	Patch-based CNN on BreaKHis dataset	Patch Extraction, CNN, Feature Learning, Image Fusion, Histopathology	Classification Accuracy: 85–90%
Automatic IDC detection in whole-slide image using CNN	Patch-based 3 layer CNN	Shallow CNN, WSI, Patch Sampling, IDC Detection, Probability Map	Balanced Accuracy: 84.23% F-measure: 71.80%

V. CONCLUSION

This study provides a comparison on different techniques used in analysis of mammary cancer using machine learning techniques. The conventional methods depends on features that are handcrafted and usually struggles with variations in straining, illumination and difficulty in identifying tissue structures. This leads to low performance of conventional methods. Former deep learning studies focused on patch based classification or segmentation but lacked in processing Whole-Slide Images(WSI) and depend largerly on expert annotations. While our proposed model overcome these limitations by combining preprocessing images, patch extraction, feature extraction, U-Net Segmentation and MIL aggregation into a single system. This makes the model to capture both fine-grained tissue details and global slide-level context. Hence the combination gives more accurate results and better performance.

A. Future Scope

Our proposed model has improved accuracy and also overcome drawbacks of previous works but still there is scope for more future development. Self-supervised and semi-supervised learning approaches is merged to reduce the dependence on large datasets and hence costs of data preparation is also reduced. The use of Vision Transformers (ViT) and hybrid CNN-Transformer models can be analysed for capturing long-range relationships in images. To gain doctor’s trust Grad-Cam and attention heatmaps can be used to highlight the regions showing cancerous cells. Testing the model in multiple hospitals and integrating it into real-time clinical workflows will improve robustness of the model and ensure reliability among patients. Finally integration with AI can give faster results with higher accuracy and the model is accessible globally.

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