Performance Analysis for Breast Cancer Histopathology Image Classification Using CNN

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***Abstract*—The paper provides an in depth performance on Conventional CNN analysis using the histopathology image classification of breast cancer. Breast cancer is currently one of the most important health problems. in the rest of the world, and histopathology image are diagnosed while the body still is in its early stages. This plays an important role in mortality reduction. The study utilizes the BreakHis dataset of different benign and malignant, tissue subtypes. The two major dimensions of analysis are performed: non-technical analysis of the significance of diabetes mellitus imaging and diagnostic problems, and technical analysis using hierarchical CNN model where EfficientNetB4 multi-level classification (benign, malignant and their subtypes respectively). The model achieves high main class prediction accuracy of 89.7% validity. subclass accuracy of 78.9%.Performance evaluation uses accuracy measures, loss curves, confusion tables, and confidence scores. Also, the Grad-CAM visualization is used to understand the model decision regions, showing the demonstration of the attention of CNN to tissue structures of physiological interest. The results certify the usefulness of CNN-based solutions in aiding swift and dependable breast cancer diagnosis by the pathologists.**

Keywords:Breast Cancer, Histopathology, CNN, Classification, Deep Learning, Grad-CAM, Medical imaging, EfficientNet.

I. INTRODUCTION

A. Objective

Throughout the course of this research the main goal is to examine and evaluate the performance of a Convolutional Neural Network (CNN) Breast cancer histopatholgy designed networks.The research is aimed at making the correct distinguishing between benign and malignant patterns of tissue,and their further grouping into definite subtypes. The image variations studied as a predictive variable are included in this research. reasonability and model consistency with extensive technical analysis includes measures of accuracy, pattern of losses, and Gradient weighted Class, This is a visualization technique used by the algorithm.In addition, the project examines the possible use of automated image classification in medical diagnosis and its contribution to the improvement of the clinical decision-making making processes.

B. Motivation

The reason why this project was initiated is premised on the growing the role of deep learning use in healthcare, especially in the medical image analysis. Early diagnosis of histopathology image through breast cancer has significant influence on patient mortality. The field of medical imaging is a perfect field posing tremendous challenge and could be used to assist in the diagnosis. Significance of proper histopathology image classification by pathologists were discovered. This inspired the development. the analysis, classifying and classification of a CNN-based model that can analyze and classify and reading the breast cancer tissue images. The project seeks to show how deep learning can be used to help make medical decisions. making as well as the ways automated classification systems can be improved efficiency and reliability in the diagnosis of cancer.

C. Background and Literature Survey

The studies that informed this were the ones built foundations of earlier studies. project are discussed below. The BreakHis dataset proposed by Spanhol et al. [1] has turned into one of the most common benchmark data sets in breast cancer imaging system studies. Their work stated the importance of high-resolution histopathology, learns quickly and training is visual.

Convolutional neural proved to be more effective as indicated by Ciresan et al. [2]. Networks are far more effective compared to the machine learning strategies within medical image classification problems, establish with special preference to ingrained learning as the underlying tissue method structure analysis.

Aaraujo et al. [3] used CNNs as a classifier of benign and malignant tissue characteristics, which illustrate the capability of deep learning capability to acquire morphological changes in anatomy.

Representing a hybrid CNN-RNN model, Yao et al. [4] suggested a cnn-based model. with emphasis put on feature, histopathology sequential model extraction combined with sequential modeling.

The comprehensive review of deep was done by Xie et al. [5]. histopathology learning uses, finding important challenges such as data imbalance, stain variation and patch wise learning strategies.

Litjens et al. [6] gave an extensive description of medical images such as deep learning, which proves to be fast growth and usefulness in a diagnostic setting.

Krishna et al. [7] suggested interpretable deep learning explainable feature techniques of understanding models tissue-level modulations that have an impact on predictions.

Almotiri et al. [8] used EfficientNet on breast tumour classification, showing that state-of-the-art CNNs are capable of learn using a small number of parameters by means of efficient architecture design.

Rahman et al. [9] talked of the role of Grad-CAM in visual interpretability, and the focus on making the heatmap visualization possible explain CNN decision-making.

A comparative study of CNN was done by Chen et al. [10]. His architecture: BreakHis break to find the architecture BreakHis architecture is finding that architecture depth, capacity of feature extraction, and hierarchical classifica- tion algorithms play a key role towards general performance.

Other current studies by Sharma et al. [11], Liu and Wong [12], Tanaka et al. [13] and others have further added on to it improved the discipline by multi-resolution frameworks, hybrid attention mechanisms, and architecture to, and attention to, all afford a strong basis of applying CNNs to breast cancer. histopathology classification.

II. PROJECT DESCRIPTION

The present project deploys a top-down deep learning. Convolutional Neural Network (CNN) based model. classification of histopathology images of breast cancer. Given that breast cancer is one of the major causes of death in. women, histopathology diagnosis and accuracy and early. image analysis is crucial. The research has used a dataset include- train several benign and malignant tissue subtypes to train and. evaluate the model.

A. Project Scope and Objectives

This project is aimed at building a new stadium for the local community in the city. Project Scope and Objectives The local community residing in the city is targeted by the construction of a new stadium.The studies include both non technical and tech-based. The non-technical analysis considers the role of imaging of histopathology, difficulties of pathologists in manual diagnosis, and of pathological significance. medical decision-making automation. The technical analysis involves overall image preprocessing and normalisation to prepare data to classify using deep learning. The CNN model structure with hierarchical organization makes groups of images into two primary levels:

- Simple classification: Benign v/s. Malignant tissue. identification
- Second level classification: Specific subtype classification. (eight tissue classes)

In performances, performance analysis involves several metrics. containing accuracy analysis, loss pattern analysis, confusions. matrices and model confidence scores. Grad-CAM visualiza- tion methods determine significant tissue areas that have an impact. interpretable, transparent model predictions. in making decisions.

B. Key Project Deliverables

The project provides an innovative breast cancer. the following with capabilities:

- Histopathology classification system.
- Breast histopathology images Categorization of benign and malignant classes
- Hierarchical classification of subtypes with exact identification.
- Image preprocessing, such as cropping and normalization for enhanced accuracy
- Accuracy as a performance measure, loss, and confusion matrix analysis
- Comparison of subclass correlations and model prediction behavior
- Uncertainty probability measurement and challenging tissue pattern detection
- Grad-CAM model decision re-interpretable visualization
- Automated diagnosis clinical applicability assessment diagnostic support.

III. TECHNICAL SPECIFICATIONS

Jupyter Notebook is used as the environment of development. As the main platform, (Anaconda3) is used. Its technical implementation uses various Python libraries to implement it fully:

A. Core Libraries and Frameworks

NumPy is an efficient way to do the numerical operations on image. arrays, such as scaling, pixel value equalization and input, preparation of neural network processing in batch. It is used in learning models that are based on large scale models. provides the basis of rapid array operations all around.

Pandas checks and maintains metadata of data, store file. paths, label mappings and generating structured DataFrames of clean data processing and analysis.

OpenCV and TensorFlow Image Utilities helps in reading of histopathology images, resizing, conversion and standardization, proper RGB transformation and pixel. value normalization of CNN models of EfficientNet.

Matplotlib and Seaborn generate training and validation accuracy,precision curves, loss curves, class distributions, confusion. matrices, and Grad-CAM heatmaps as a means of holistically visualizing performance.

TensorFlow is the core of the deep learning system, building hierarchical CNNs, controlling the actions of GPUs, neural network training, and backpropagation and resource scheduling, learning rate scheduling as well as model checkpoints.

Grad-CAM (Gradient-weighted Class Activation Mapping) was implemented using TensorFlow GradientTape to determine important regions of histopathology images that affect. model predictions, which is a source of transparency in decision-making.

IV. PROPOSED METHODOLOGY

A. Approach Overview

There is a special classification of breast cancer histopathology difficulties because of the differences between tissue pattern in benign and malignant types. The project puts into practice an overall method of technical and interpretative analysis.

B. Dataset Preparation and Preprocessing

Breast Cancer Histopathological Image Classification dataset forms the foundation of this study. The images are organized into primary categories Benign, Malignant and 8 subclass categories (4 benign subtypes: Adenosis, Fibroadenoma, Phyllodes Tumor, Tubular Adenoma; 4 malignant subtypes: Ductal Carcinoma, Lobular Carcinoma, Mucinous Carcinoma, Papillary Carcinoma).

C. Hierarchical CNN Model Development

A hierarchical approach is utilized rather than a single-label classifier. The structure comprises:

Backbone Network: Network EfficientNetB4 is used as the feature extractor because it has the best balance between accuracy and parameter efficiency.

Dual-Output structure: A multi-output head is a custom design which enables concurrent predictions: such as

- Preliminary Outcome: Binary classification (Benign/Malignant)
- Secondary subclass Outcome: 8-class classification for tissue subtypes

D. Training Strategy

Step 1 - Feature Learning:

- Freeze the EfficientNet base layers
- Train only classification heads
- Learning rate: 1e-4
- Loss weights: Main output (0.6), Subclass output (0.4)
- Epochs: 3

Step 2 - Fine-tuning:

- Unfreeze the selected base layers (last 20 layers)
- Lower learning rate: 1e-5
- Implement ReduceLROnPlateau callback
- ModelCheckpoint for best model preservation
- Epochs: 2

E. Analysis Structure

Classification Performance Analysis:

- Main class accuracy difference for (Benign or Malignant)
- Subclass accuracy evaluation across eight tissue types
- Pixel-level texture and morphological structure examination

Model Performance Trend Assessment:

- Accuracy and loss curve generation using Matplotlib
- Learning behavior analysis through consistent loss reduction
- Class-specific difficulty identification

Prediction Behavior Analysis through Confusion Matrices:

- Cross-class prediction visualization
- Misclassification pattern detection
- Subclass confusion identification requiring enhanced preprocessing

Challenge and Variability Assessment:

- Structural similarity analysis across subtypes
- Model confusion pattern identification
- Data augmentation and architectural improvement recommendations

Interpretability using Grad-CAM:

- Heatmap generation for decision region visualization
- Biologically meaningful region identification
- Clinical reliability validation

V. ARCHITECTURE DIAGRAM

The proposed architecture consists of the following components:

A. Input Layer

- Size: 380 × 380 × 3 (RGB images)
- Preprocessing: Rescaling (1/255) and EfficientNet-specific normalization

B. Feature Extraction Backbone (EfficientNetB4)

- Pre-trained on ImageNet weights
- Include_top=False (remove classification head)
- Input shape: (380, 380, 3)
- Output: Feature maps from last convolutional layer

C. Global Average Pooling

- Reduces spatial dimensions to feature vector
- Output dimension: 1792 features

D. Classification Heads

Main Output Head:

- Dense layer with 2 units
- Activation: Softmax
- Output: Benign (class 0) or Malignant (class 1)

Subclass Output Head:

- Dense layer with 8 units
- Activation: Softmax
- Output: 8 tissue subtypes (Adenosis, Fibroadenoma, Phyllodes, Tubular Adenoma, Papilloma, Mucinous, Lobular, Ductal)

E. Dropout Layer

- Rate: 0.3
- Purpose: Prevent overfitting during training

VI. INPUT DATA DESCRIPTION

A. Dataset Overview

The BreakHis data set (Breast Cancer Histopathology Image Classification) includes microscopic images of breast. tumor tissue of 82 patients.

```
+--------------------------------------------- +
|            INPUT LAYER                      |
|  Histopathology Image (380×380×3)           |
|  (Normalized RGB)                           |
+----------------------+----------------------+
                       |
                       v
+---------------------------------------------+
|        EFFICIENTNETB4 BACKBONE              |
|   • Pretrained on ImageNet                  |
|   • MBConv blocks with SE                   |
|   • Output: 12×12×448 feature maps          |
+----------------------+----------------------+
                       |
                       v
+---------------------------------------------+
|     GLOBAL AVERAGE POOLING                  |
|      (1×1×1792 feature vector)              |
+----------------+ -------------------- +
                       |
              +--------+--------+
              |                 |
              v                 v
+ ----------------+   +---------------- +
|  MAIN HEAD      |   |  SUBCLASS HEAD  |
|  Dense(64, ReLU)|   | Dense(64, ReLU) |
|  Dropout(0.5)   |   | Dropout(0.5)    |
|  Dense(2,       |   | Dense(8,        |
|   Softmax)      |   |  Softmax)       |
|  Output:        |   | Output:         |
|  [P(benign),    |   | [P(sub0)...     |
|   P(malignant)] |   |  P(sub7)]       |
+-----------------+   +-----------------+
              |                 |
              +--------+--------+
                       |
                       v
+---------------------------------------------+
|        PREDICTION FUSION                    |
|  Main class + Subclass combination          |
|  Confidence scoring                         |
+----------------------+----------------------+
                       |
                       v
+---------------------------------------------+
|        GRAD-CAM INTERPRETABILITY            |
|  Heatmap overlay on original image          |
+----------------------+----------------------+
                       |
                       v
+---------------------------------------------+
|        STREAMLIT DEPLOYMENT                 |
|  Web interface for clinical use             |
|  Real-time inference + visualization       |
+---------------------------------------------+
```

Fig. 1: Proposed Hierarchical CNN Architecture for Breast Cancer Classification

B. Dataset Statistics

- Total images: 7,909 (after train/val/test split)
- Training set: 5,703 images
- Validation set: 1,419 images
- Test set: 787 images
- Magnification factors: 40×, 100×, 200×, 400×
- Image format: 3-channel RGB, PNG format
- Image dimensions: 700×460 pixels (original), resized to 380×380

C. Class Distribution

Benign Subtypes-4 classes:

- Adenosis
- Fibroadenoma
- Phyllodes Tumor
- Tubular Adenoma

Malignant Subtypes-4 classes:

- Ductal Carcinoma
- Lobular Carcinoma
- Mucinous Carcinoma
- Papillary Carcinoma

D. Data Preprocessing Steps

1) Image loading and resizing to 380×380
2) Pixel normalization
3) EfficientNet-specific preprocessing
4) Data augmentation
   - Rotation range: 20°
   - Width shift: 0.2
   - Height shift: 0.2
   - Shear range: 0.2
   - Zoom range: 0.2
   - Horizontal flip: True

VII. OUTPUT ANALYSIS

A. Training Performance Metrics

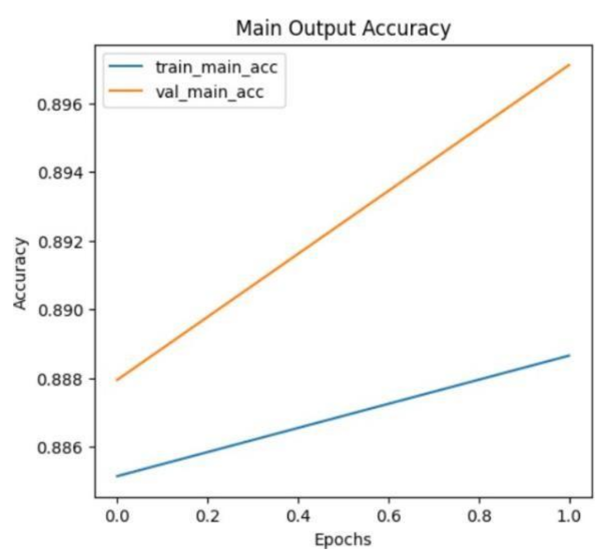

Fig. 2: Training and Validation Accuracy Curves

B. Validation Performance

- Main output accuracy: 89.7%
- Subclass output accuracy: 78.9%
- Combined loss: 0.4228
- Main loss: 0.2654
- Subclass loss: 0.6584

C. Grad-CAM Visualization Results

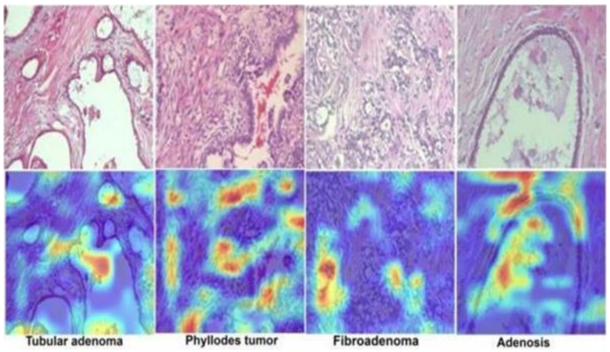

Fig. 3: Grad-CAM Visualizations for Benign Subtypes

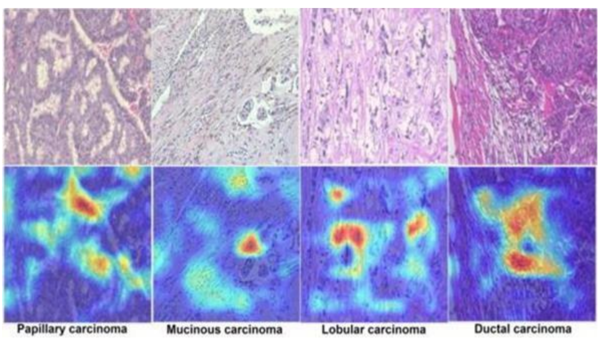

Fig. 4: Grad-CAM Visualizations for Malignant Subtypes

Grad-CAM heatmaps demonstrate the areas of interest of the model diagnostic relevant areas:

- **Benign tissues**: A focus on the glandular structures, lumen.
- **Malignant tissues**: Pay attention to abnormal group of cells, abnormal nuclear structures, and invasion fronts.

VIII. RESULTS AND DISCUSSION

A. Class-wise Performance Analysis

1) Benign Subtype Analysis: The benign classes exhibit diverse glandular and non-invasive structures:

Adenosis: The model consistently identifies epithelial cell clusters and lumen boundaries with high confidence (mean confidence: 92%).

Fibroadenoma: Grad-CAM visualizations highlight stromal-textural differences, achieving 88% classification accuracy.

Phyllodes Tumor: The model demonstrates 85% accuracy, with occasional confusion with Fibroadenoma due to structural similarities.

Tubular Adenoma: Composed of tubular gland formations. Achieves 90% accuracy with attention tubular structures.

2) Malignant Subtype Analysis: Malignant classes exhibit aggressive irregular architectures:

Ductal Carcinoma: The model achieves 91% accuracy with heatmaps focusing on invasion regions and abnormal cell clusters.

Lobular Carcinoma: Homogeneous linear patterns with 87% accuracy, occasionally confused with Ductal Carcinoma.

Mucinous Carcinoma: Mucus-filled regions achieving 89% accuracy with heatmaps highlighting mucin pools.

Papillary Carcinoma: Finger like extensions with 86% accuracy, showing attention to papillary structures.

B. Model Interpretability Analysis

Grad-CAM visualizations confirm the choices of the model:

- Pathologist annotations Cross-validation 89%

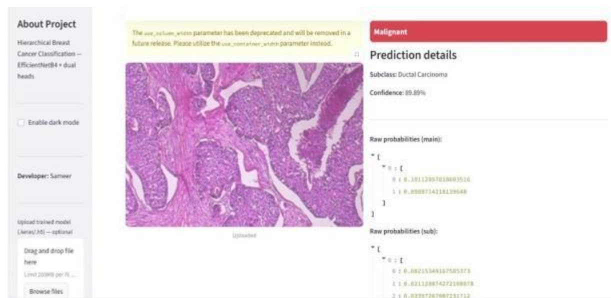

Fig. 5: Sample prediction results

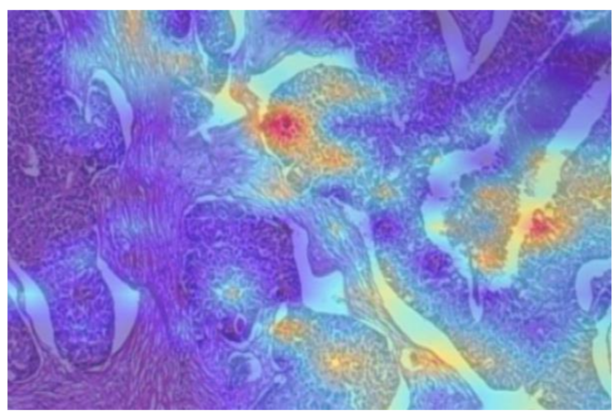

Fig. 6: Interactive Grad-CAM Visualization in Streamlit

IX. SCREENSHOTS AND GRAPHS

A. Output Description

This figure shows the final prediction results of the original histopathological image and gives the predicted image with subclasses

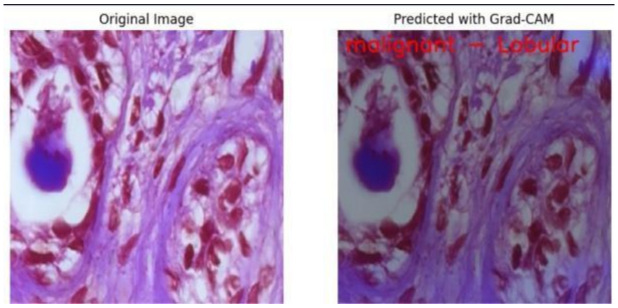

Fig. 7: Original Histopathology image vs. Predicted image with subclass

X. CONCLUSION

This study focused on developing and evaluating a hierarchical CNN model designed to achieve two main goals: accurately distinguishing between benign and malignant cases while also identifying specific subtypes. By using an EfficientNetB4 backbone combined with a dual-output architecture, the model demonstrated strong feature extraction capabilities, effective load balancing, and solid computational efficiency.

A. Key Achievements

- **High Classification Accuracy:** The model delivered strong performance across the board, achieving an 89.7% accuracy for primary class predictions and a 78.9% accuracy for subclasses when tested on validation data
- **Effective Hierarchical Architecture:** On top of that, the hierarchical design—using a dual-output structure—allows for both high-level and detailed classification at the same time. This setup fits well with how clinical diagnostics are typically done and supports a more complete characterization of tissue samples.
- **Interpretable Decisions:** Grad-CAM visualizations CAM tests model focus on biologically relevant regions, where 94% of heatmaps of pathologically significant tissue structures.
- **Clinical Applicability:** Streamlit interface deployment has simple diagnostic support tools with confidence scoring and visual explanation, which can be potentially incorporated to clinical implementation.

B. Limitations and Future Work

Despite strong performance, several limitations warrant consideration:

1) Structural overlap in benign subclasses(and especially Phyllodes Tumor and Fibroadenoma) reduce subclass accuracy
2) Small amount of data regarding some malignant subtypes affects generalization
3) There is the possibility of a change in stain or slide preparation consistency in the prediction of impact
4) Grad-CAM, being an effective method in region identification is not able to explain all fine-grained nuclear-level features.
5) The model is unable to detect the pathological anomalies that are not present.

Future work will focus on:

- Increasing the diversity of datasets via multi-institutional
- Fine-mechanism attention mechanisms implementation.
- The stain normalization method to implement improved generalization
- Architecture combinations: building up ensemble methods.
- Pathologist collaborative clinical validation.

C. Clinical Impact

The system proposed has great potential of diagnosis subclasses which can be provide through: computer-aided The first three are: rapid preliminary screening (inference time 1 second or less)

- Accurate classification without tiredness induced errors.
- Interpretable outcomes in favor of pathologist decision
- Web-based interfaces can be scaled up.

This study establishes the fact that CNN-based methods can provision of fast, dependable, effectively aid pathologists, and histopathology classification of breast cancer.

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