Breast Cancer Detection Using Convolutional Neural Network

Eshita Yadav
Department of Information Technology
KIIT University
Bhubaneshwar, India
krishneteshita@gmail.com

Anshika Kashyap
Department of Information Technology
KIIT University
Bhubaneshwar, India
anshikakashyap92631@gamil.com

Abstract- **Breast cancer represents the most dangerous female cancer type that exists throughout the world as one of the prevalent diseases. The successful treatment along with improved survival rates becomes achievable through early breast cancer detection. The research establishes a CNN system to perform automatic breast cancer diagnostic tasks. The system trains with mammography photos to receive measurements of accuracy ratings and precision levels and recall measurements as well as F1-score measurements. Medical image classification reaches high levels of performance through CNN-based deep learning methods which demonstrate according to research outcomes.**

Keywords— **Breast Cancer, Convolutional Neural Network, Deep Learning, Medical Imaging, Image Classification, Machine Learning, Tumor Detection**

I. INTRODUCTION

Breast cancer stands among the most widespread causes of death among females which exist across all regions of the world. Radiological manual examinations conducted by experts lead to prolonged examination times and open space for human misdiagnosis. The development of automatic and precise medical image classification results is attributable to deep learning technology through its particular Convolutional Neural Networks (CNNs). The study evaluates CNNs as diagnostic equipment that uses digital mammogram images to identify breast cancer.

II. METHODOLOGY

A. Dataset Description

The training model receives mammogram images that belong to either the benign or the malignant categories. The medical imaging resources openly accessible provided the dataset that contains detailed grayscale images. Technicians provide professional diagnosis labels for every image included in the dataset. The dataset needs balanced learning thus it undergoes class balancing procedures which combine minority class oversampling with weighted loss functions. The dataset partitions its content into three sets -- training, validation, and test -- according to a distribution ratio of 80:10:10 for model generalization assessment.

B. Data Preprocessing

Images require preprocessing before a CNN can effectively extract features out of them. The following steps are applied:

- Resizing: The images receive treatment through uniform resizing to standard 224 × 224 pixels and normalization applies scaling to [0,1] for pixel intensity values.
- Normalization: The pixel intensity values receive normalization scaling to [0,1] range which helps training converge effectively.
- Data Augmentation: The dataset receives multiple augmentation techniques including rotation and flipping together with zooming and brightness modification to increase its diversity and decrease overfitting.
- Noise Reduction: Gaussian filters eliminate unwanted image noise through noise reduction procedures to enhance clarity.

C. CNN Model Architecture

The Convolutional Neural Network (CNN) functions to obtain image spatial information which enables it to identify between benign and malignant categories. The architectural model contains multiple identifiable sections which include:

1. Convolutional Layers:

- The 3×3 kernels extract features from images while using ReLU activation.
- The network employs different convolutional layers to construct an increasing arrangement of features.

2. Pooling Layers

- Max Pooling (2×2) serves to maintain crucial features while it lowers the spatial dimensions of the image.

3. Dropout Layers

- A dropout rate of 0.5 is utilized because it randomly deactivates neurons to stop the model from overfitting while training.

4. Fully Connected Layers

- After flattening the extracted features they pass through dense layers using ReLU activation.
- The last layer utilizes a softmax activation function which performs two-category image classification.
- A softmax activation function in the final layer classifies images into two categories.

D. Training and Hyperparameters Optimization

Training process uses Adam optimizer at 0.001 initial learning rate. The model makes use of Categorical Cross-Entropy to calculate its loss function. The performance optimization implements these additional methods:

- The learning rate scheduling technique reduces the learning rate as validation accuracy reaches a steadystate condition.
- Early Stopping terminates the training process if validation loss stops improving during the defined number of training epochs.
- The implementation of stable gradient updates relies on selecting a batch size of 32.

E. Model Evaluation Metrices

The model performance gets evaluated through these evaluation metrics:

- Accuracy tracks the number of images that the model correctly labels.
- Precision & Recall: Evaluates the model's ability to correctly identify malignant cases.
- F1-Score: Balances precision and recall for an overall performance measure.
- Confusion Matrix: Visualizes the distribution of correct and incorrect classifications.

III. Results and Discussion

A. Data Preprocessing

The trained model achieves high accuracy in classifying breast cancer images. Evaluation metrics such as precision, recall, and F1-score are analyzed to assess model reliability.

B. Evaluation Metrics

The model performance is evaluated using the following metrics:

- Accuracy: The ratio of correct positive predictions to entire predicted positives defines the precision calculation. The detection of true positive cases in the population is measured through recall.
- Precision: Represents the ratio of correctly predicted positive observations to total predicted positives.
- Recall: Indicates the ability to correctly identify positive cases.
- F1-Score: The harmonic mean of precision and recall.

IV. CONCLUSION

The thorough investigation shows that CNN-based deep learning models serve efficiently for breast cancer identification tasks. The classification model operates effectively for breast cancer diagnosis while assisting medical experts in their diagnostic processes. The upcoming stages of improvement should involve combining various data types together with techniques to improve explanatory framework competence.

V. FUTURE WORKS

Future development of this CNN model entails architecture modification alongside testing of transfer learning models like DenseNet and ResNet as well as explainability method integration for increased model clarity.

VI. ACKNOWLEDGEMENT

KIIT University together with Jyoti Prakash Meher their teacher provided all the required research material for this investigation to the authors. The authors sincerely thank their professors along with peers whose beneficial guidance proved essential to finishing their research work successfully.

VII. REFERENCES

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