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# Classification of Mammography Images Using Deep-CNN based Feature Ensemble Approach and its Implementation on a Low-Cost Raspberry Pi

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**Abstract:** Deep Convolutional Neural Network (Deep-CNN) algorithms have demonstrated superior performance over different machine learning approaches in the early-stage detection of breast cancer using mammography images in recent years. These algorithms have aided radiologists in detecting suspicious breast masses and other key characteristics in mammography images with greater accuracy. However, the accuracy of such deep learning models in detecting breast cancer highly relies on a number of factors like the quantity and quality of mammography images, the methodology used to extract abstract features, the selection of network architecture, and the appropriate hyperparameters for a chosen deep learning strategy. Incorrect selection of such factors might lead to unsatisfactory results in breast cancer diagnosis and prediction. The ensemble CNN designs have demonstrated their effectiveness in enhancing model performance intended for complex disease analysis. Our paper aims to create an ensemble Deep CNN-based mammography image classification model by concatenating the features extracted by VGG16, VGG19 and ResNet-50 pre-trained CNNs. The ensemble features are classified with an ensemble machine learning classifier frame (Support Vector Machine, K-Nearest Neighbor, Decision Tree, Random Forest, Gaussian Naive Bayes) to classify the mammography images. The results obtained with our proposed model are compared with existing DL-based breast cancer detection methods using two publicly accessible mammography datasets [Mammographic Image Analysis Society (MIAS), Digital Database for Screening Mammography (DDSM)]. The blend of ensemble CNNs as feature extractors and ensemble machine learning classifiers resulted in classifications of breast masses into binary as well as multi-class with better accuracy. The proposed model outperformed some of the existing models by achieving 96% accuracy with DDSM and 99% accuracy for MIAS datasets. The paper also describes the workflow of deploying the trained ensemble DL mammography image classification model on a Raspberry Pi 3B embedded device. The deployment of trained DL models on low-cost, low-computational embedded devices opens a wide room for researchers to develop faster and cost-effective Computer-Aided Detection systems for disease diagnosis.

**Keywords:** Breast cancer detection (BCD), Mammography images, Deep learning (DL), Convolutional Neural Network (CNN), Pre-trained CNN, Raspberry Pi (RPI)

## 1. INTRODUCTION

Breast cancer is the most prominent cancer type with a 14% rate of occurrence over other common cancers in Indian women [1]. Indian Council for Medical Research (ICMR) reported 17.3 Lakhs breast cancer cases in 2016 with a staggering rise in the upcoming years. To lower the death rate in vulnerable populations, early identification and prompt treatment of breast cancer are crucial measures. Mammography is the most recommended, safe, and cost-effective screening method to detect the presence of abnormal breast tissues in breast images compared to the other imaging modalities [2][3]. However, the low contrast of mammography images, the presence of the pectoral muscles, and the presence of local lesions make the manual interpretation of breast cancer more challenging for radiologists [4]. The progressive development of Computer-Aided Detection (CAD) systems with advanced technological avenues may always ease the job of radiologists by assisting them in making accurate detections and overcoming the challenges faced in manual interpretations [5]. Recently, Deep Learning (DL) algorithms have shown efficiency in different computer vision applications and have enthused their usage in medical image analysis [6]. Subsequently, DL algorithms are well utilized in Automated CAD system development to carry out medical image classification, segmentation, and object localization of abnormalities [7] considering different imaging modalities such as X rays, CT, MRI, PET, ultrasound etc [8][9]. DL algorithms are efficient in dealing with nonlinear medical image analysis for complex disease detection and prediction tasks pertaining to various anatomical locations,

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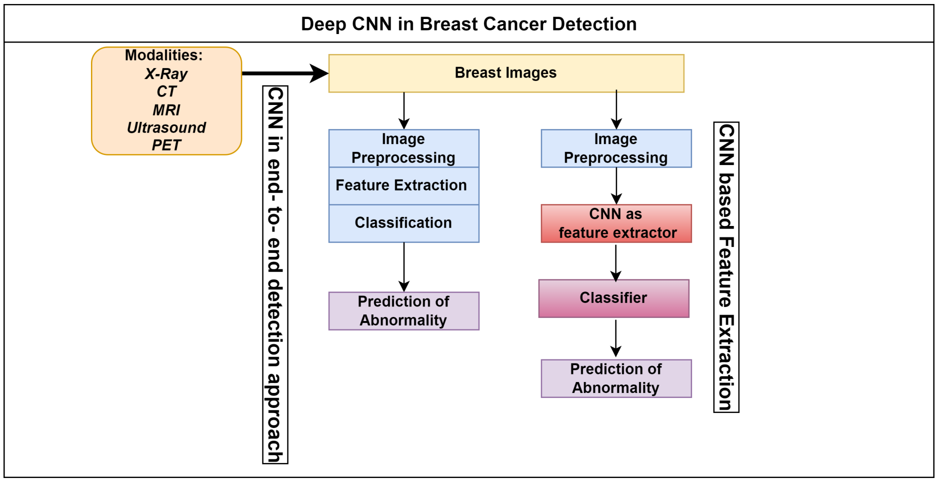


Figure 1. Deep CNN taxonomy in Breast Cancer Detection

without necessitating a great amount of hand-coding steps involved in abnormality identification taxonomy over machine learning algorithms [10]. Compared to other deep learning architectures, CNNs have demonstrated potential and superior performance in the creation of end-to-end CAD systems for medical image processing [11]. Using mammograms, CNN-based breast cancer diagnostic systems have demonstrated increased speed and efficiency in breast anomaly identification compared to the available image processing algorithms [12]. The currently available CNN-based breast cancer classification models employ pre-trained CNN either as a feature extractor or as an end-to-end classifier. In the lack of suitable preprocessing techniques applied to the raw mammograms, the use of pre-trained CNN architecture may not be able to collect all the subtle information from low-contrast mammography images. The automatic feature extraction procedure and class prediction from an image dataset performed better using a deep ensemble technique that combined more pre-trained CNN architectures but at the expense of extensive network training time [13].

Our paper aims to describe the development of a Deep CNN-based mammography image classification model with an ensemble of three simple CNNs (VGG16, VGG-19 and ResNet-50) to extract the complex features from mammography images and prediction of abnormality class of breast mass with a majority voting system applied on the ensemble machine learning (EML) classifiers (Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree (DT), Random Forest (RF), Gaussian Naive Bayes (GNB)). The proposed method has achieved better performance matrices over some of the recent works.

The deployment of DL models entails the presence of a reliable CPU/GPU with strong computational capabilities, memory with low power consumption, etc. Pre-trained/custom-trained DL models are increasingly being deployed using low-cost hardware platforms or authoritative servers (cloud) because of the possibility of simplifying the deployment procedure. However, DL models built on low-cost embedded hardware rather than web servers offer an offline, secured method of performing image inference with minimum latency. However, the selection of low-cost hardware platforms is always challenging considering their computing speed, memory size, power consumption, and cost etc.The use of several embedded platforms, such the Arduino Uno and Raspberry Pi (RPI), by the developers to deploy DL models for computer vision issues has been demonstrated successfully [14][15][16]. Due to the availability of preinstalled Python-supported development environments (Python IDE, Thonny, etc.) and the simplicity of installing highly used library packages like TensorFlow, Open CV, and Keras on RPI modules for different computer vision applications [17][18][19], it has been observed that low-cost, low-powered RPI modules are widely used. Authors of [20][21] have shown the utilization of RPI modules for implementing the successful deployment of breast cancer detection model. The availability of sufficient memory for model storage and low power consumption of RPI 3B over higher versions has encouraged us to use it for mammography image classification trained model deployment for breast mass abnormality classification on test mammography images.

### A. Motivation

The taxonomy of CNN based breast classification model as shown in Figure 1 describes the taxonomy of CNN as a feature extractor or in end to end detection. The potential of CNNs in extracting the semantic features from the images has given leverage to use them as feature extractors [22] with scratch learning [23] or the transfer learning (TL) approaches [24][25][26]. Scratch learning typically demands the developer's expertise in creating the customized network and setting the network hyperparameters. Whereas, TL approach uses pre-trained CNN models to learn new task-specific features with very small refinements in the network architecture and hyper parameters. Certain pre-trained CNN architectures like Xception, Inception-V3, VGG16, VGG19 and ResNet-50 with TL approach have demonstrated their efficiency in image classification tasks [27][28]. Nevertheless, the stand-alone pre-trained CNN may not capture all the semantic characteristics from the images and thus affects the model accuracy in generalizing the test images. Ensemble of different CNN architectures have shown their potential in extracting key characteristics of medical images [29][30][31]. Although ensemble models have strengthened the feature extraction process from mammography image classification task and shown higher accuracy, certain issues that need to be addressed are mentioned as follows.

- Mammography images contain contrast variances that in the absence of suitable image preprocessing techniques, potentially result in inadequate feature extraction. Hence selection of suitable image preprocessing steps is pivotal in defining the model accuracy in the prediction and detection of abnormality.
- Performing training with segmented Region of Interest (ROI) from mammography images can boost the efficiency of the network in abnormality detection. However, the unavailability of the mammography datasets with image masks poses a limitation in using a segmented approach to classify the breast mass.
- Ensemble of different pretrained CNNs tends to generate a large feature vector from a mammography image, which would necessitate higher hardware memory allocation to store the feature vector. The selection of an appropriate pre-trained model is necessary to maintain a balance between memory requirements to store the ensemble feature vector and to determine the model's efficiency to predict the classification score.

### B. Contribution

The proposed model ensembles features extracted by three different pre-trained architectures VGG16, VGG19 and ResNet-50 to perform binary or multiclass classification of breast masses. The ensemble feature vector is classified with an EML classifier frames constituted with SVM, RF, DT, GNB and KNN machine learning classifiers. The majority voting system is incorporated to determine the classification category based on the majority vote generated by classifiers for a particular task. Our contributions are described below.

- Image enhancement of Mammography datasets (MIAS [32] DDSM (Images with Mediolateral Oblique (MLO) and Craniocaudal (CC) views) [33]) is performed using Normalized- Contrast Limited Adaptive Histogram Equalization (N-CLAHE).
- The trained model is developed with an ensemble of pre trained CNNs (feature extraction phase) and an ensemble of different machine learning classifiers (classification phase).
- The majority voting system is incorporated to generate the final classification score based on the classification score generated by different classifiers.
- The deployment of trained mammography image classification model is governed on a low-cost Raspberry Pi 3B (RPI 3B) device to execute the testing phase.

The organization of the paper in the subsequent sections includes related work carried out using Deep CNN (DCNN) in breast cancer detection (Section 2), the workflow of the proposed model (Section 3). The simulation results with/without Deep ensemble models are discussed in Section 4. The future directions for the enhancement of the proposed work and the conclusion are discussed in Section 5.

## 2. RELATED WORK

The important publications describing the application of DCNN in mammography image-based breast cancer detection are described below.

Imran et. al. (2022) proposed a segmentation approach to perform mammography image classification with the deep ensembled model created with long short-term memory (LSTM) and CNN architectures. Mammography images obtained from MIAS and Breast Cancer Digital Repository (BCDR) datasets were preprocessed, and ROI extraction was performed by Gaussian filter. The simulation result showed 0.994% accuracy with MIAS dataset [34].

Hekal et. al. (2022) applied a transfer learning approach to create deep ensembled model using pre-trained models (Alexnet, ResNet-50 ,ResNet-101, DenseNet-201) and SVM as a classifier to classify Malignant and Benign masses along with nodules in the Curated Breast Imaging subset (CBIS) and DDSM images with a classification accuracy of 94% in mass detection [35].

Ragab et al. (2022) developed an early-stage cancer detection system with a DCNN ensemble model with ultrasound images. The images were preprocessed and segmented initially. Feature extraction from segmented images was carried out with ensembled deep learning models (VGG16+VGG19+ SqueezeNet). The extracted features are classified with multilayer perceptron and CSO (Cat Swarm Optimization) with 97.09% accuracy [36].

Salma et. al (2021) proposed an automated approach to perform the binary classification of breast masses with several pre-trained models (InceptionV3, DenseNet121, ResNet50, VGG16 and MobileNetV2) using MIAS and DDSM mammography databases. The images were segmented using U-net and classified into Benign and malignant classes. The results obtained from DDSM images demonstrated 98.87% accuracy with U-Net and InceptionV3 combination [37].

Malebary et al. (2021) developed an automated approach to classify mammography masses by an ensemble of ResNet-50 (to extract low level features) with RNN LSTM (to extract high-level features) using MIAS and DDSM dataset.. The feature vectors were concatenated and classified into three classes (Malignant, Benign Normal) with RF clas-

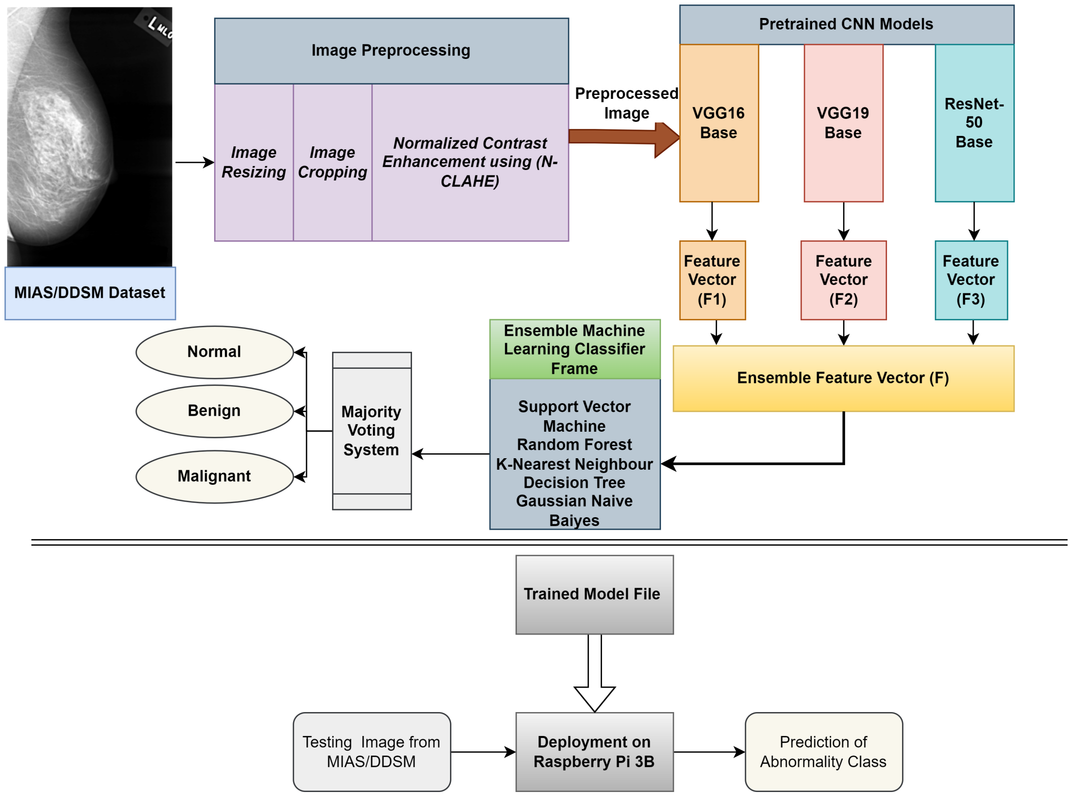


Figure 2. Workflow of the proposed deep ensemble breast cancer detection model and its deployment on RPI 3B

sifier [38]. The achieved simulation results demonstrate 0.96% accuracy for DDSM dataset and 0.95% accuracy for MIAS dataset.

Kang et al. (2021) assessed the efficiency of Deep CNN to identify the microcalcification in 1579 collected breast images (collection Duration: 2007 to 2019) with five different DCNNs (ResNet-100, Xception, Inception-V3,Inception ResNet-v2,Densenet-201 )and ensembled model formed with these pre-trained models. The highest AUC of 0.86 with ensembled model and minimum AUC of 0.79 was observed with Inception-V3 [39].

Shen et. al. t (2019) Breast cancer detection system with end to end CNN approach. With CBIS, DDSM and InBreast datasets. With CBIS DDSM dataset they could achieve AUC of 0.86. With a single CNN model and 0.91 with an averaging of the four model CNN approach. With InBreast dataset they could achieve AUC of 0.95. With a single CNN model and 0.98 with an averaging of the four model CNN approach [40].

Charan et al. (2018) used a scratch learning approach to perform binary classification of breast masses on the MIAS dataset. After the preprocessing steps of MIAS dataset images, the model accuracy was examined with CNN with different sizes of image kernels. The results obtained in their study demonstrated the efficacy of CNN in mammography image classification [41].

The effectiveness of CNN in early breast cancer detection is observed in the experimental articles cited above. The existing DCNN pre-trained models have given the ease to the researchers to use these models in medical image analysis of different modalities. The necessary amendments in pre-trained DCNN models and the selection of the right hyperparameters have proved successful in improving the performance metrics of existing models. The blend of CNN with different machine learning classifiers has shown efficiency in breast cancer detection.

### *A. Research Gap*

The use of the Deep CNN ensemble approach with one or two machine learning classifier models is demonstrated in the reviewed works. Our work intends to develop a deep CNN-based feature ensemble model to extract the features using mammography images and classify them using an EML classifier. It also demonstrates the deployment of a trained deep ensembled model on the low-cost Raspberry Pi 3B to govern the testing of mammography images with the trained model.

TABLE I. MIAS/DDSM Dataset Mammography Images

| Sr. No. | Mammography Dataset | Image type | Image Pixels | Total Image samples | Abnormality remark |
|---|---|---|---|---|---|
| 1 | Mammographic Imaging Analysis Society (MIAS) [42] | PGM images | 1024x1024 pixels | Benign Mass: 1000 Images<br>Malignant Masses: 1000 Images | Contains labeled information about different abnormality types and their severity |
| 2 | Digital Database for Screening Mammography (DDSM) [43] | PNG images | 299x299 pixels | Benign Mass: 2000 Images<br>Malignant Masses: 2000<br>Normal Masses:2000 Images | MLO and CC view of normal, benign, and malignant cases with ground truth validation |

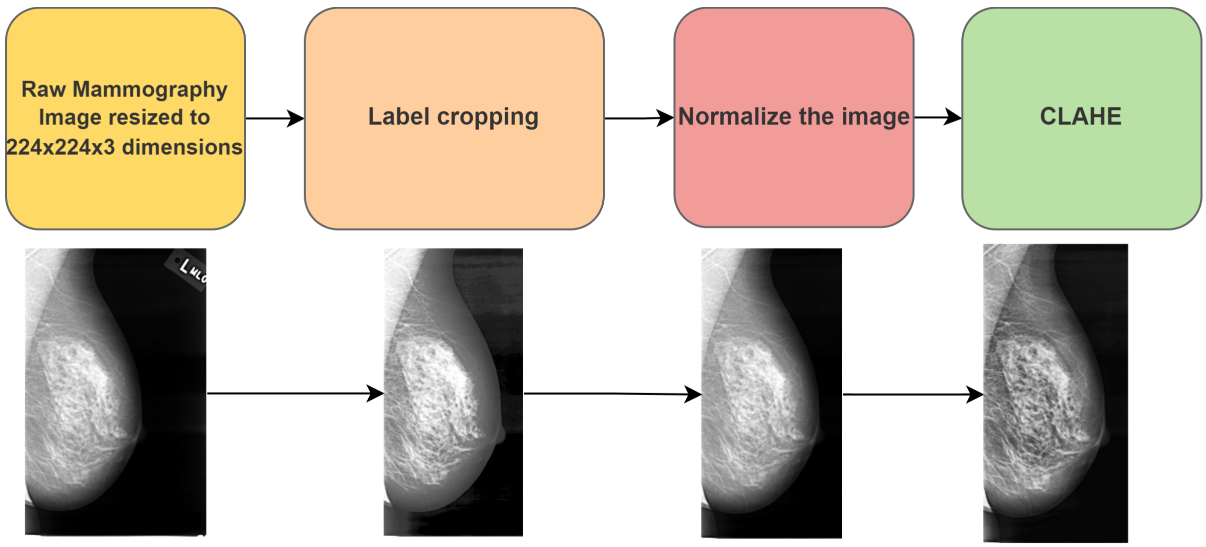


Figure 3. Image Preprocessing steps applied on Mammography Images

## 3. WORKFLOW OF THE PROPOSED DEEP ENSEMBLE BREAST CANCER CLASSIFICATION MODEL AND ITS DEPLOYMENT ON RPI 3B:

In this section, we present the development of the deep ensembled model to detect breast cancer Using MIAS and DDSM Mammography Datasets with a Fixed Feature Extraction Approach. As feature extractors, we have used the pre-trained models VGG16, VGG19, and ResNet-50 with a frozen convolutional base. The extracted feature vectors F1,F2 and F3 are concatenated (F) and classified with an EML classifier model (Fusion of SVM, RF, KNN, GNB, NV, DT) to determine the final classification score based on the majority voting system. The trained model is deployed on RPI 3B model only to test the mammography images for the class prediction. Figure 2. shows the workflow of the proposed breast cancer detection system with a deep ensembled model and its deployment on RPI 3B.

### *A. Mammography Datasets*

Table I describes about the mammography image specifications obtained from MIAS and DDSM datasets.

### *B. Mammography Image Preprocessing*

Low contrast levels in raw mammography images are seen with background tissue intensity that is extremely close to the abnormality. This creates a barrier to the machine learning model's ability to predict the anomaly class accurately. Hence raw mammography images are processed before being supplied to train the Deep CNN model. The raw images are resized, cropped to eliminate unnecessary labels, and contrast is enhanced using Normalized- Contrast Limited Adaptive Histogram Equalization (N-CLAHE) [44]. The preprocessing steps applied to a raw image are shown in Figure 3. The images are resized to 224x224x3 to make it compatible with input dimensions accepted by VGG16, VGG19 and ResNet-50. The area is calculated for each component present in an image with boundaries of structures. The image mask is applied to the original image to create the cropped image. The intensity variations existing in a mammography image are corrected with image normalization where Log of an input image is obtained first and thereafter the intensity values are rescaled between 0 to 255. To describe the image enhancement steps mathematically, let the input image be $x$, and the transformed image $y$ would be

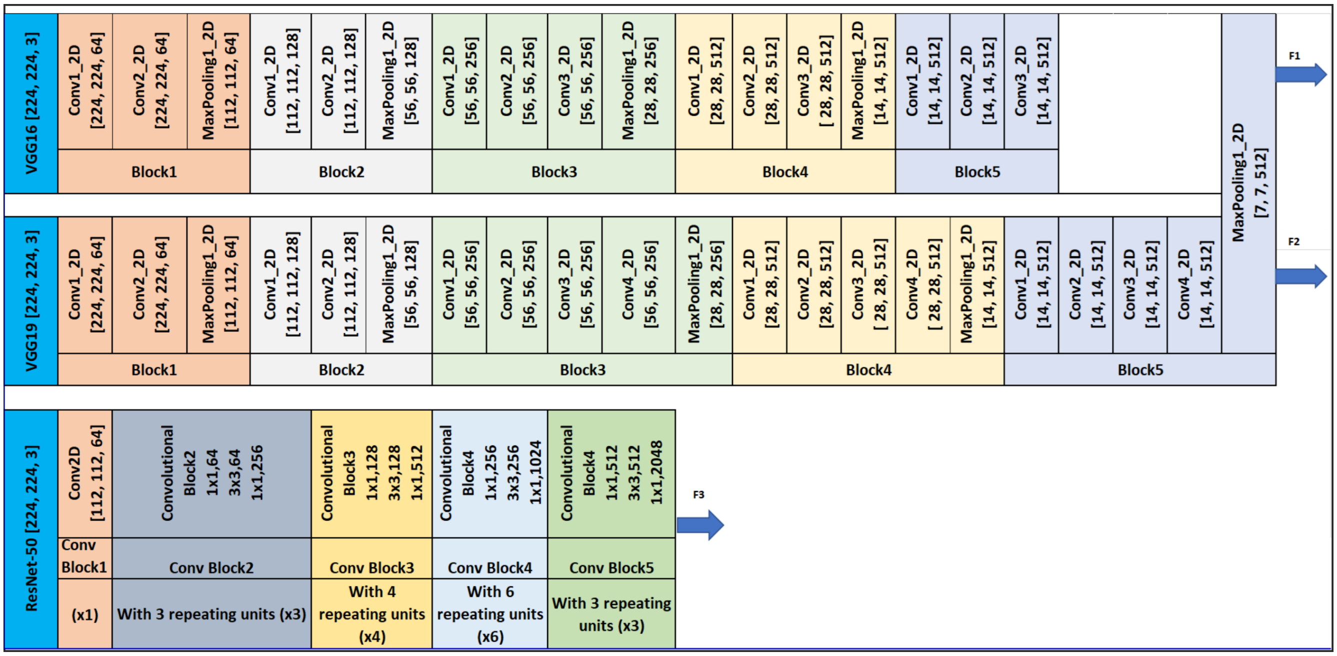


Figure 4. Layered architectures of VGG16, VGG19 and ResNet-50

$$y = Log(x) \tag{1}$$

$$y_{norm} = 255 * ((y - y_{min})/(y_{max} - y_{min})) \tag{2}$$

where, $y_{max}$ and $y_{min}$ are minimum and maximum intensity value of logarithmic image $y$.

An image is divided into a number of small, overlapping patches (tiles) after it has been normalized in order to perform contrast-limited adaptive histogram equalization with the proper clip-limit selection for an image contrast enhancement. Equation 3 shows the parameters affecting the image contrast level.

$$\beta = (P * Q)/M(1 + \alpha/100(S_{max} - 1))) \tag{3}$$

where, $\beta = clip - limit$, $P*Q$=Pixel numbers in each region, $M$= Grayscales numbers, $\alpha = clipfactor(0 - 100)$, and $S_{max}$=maximum slope value.

### C. Pre-trained CNN Models and feature concatenation

Pre-trained CNN Models and feature concatenation: The CNN models VGG16, VGG19 and ResNet-50 have achieved higher accuracies in image recognition tasks [45][27]. Figure 4 shows the layered architecture of VGG16, VGG19 and ResNet-50. VGG19 (19 layers) is the modified variant of VGG16 (16 layers) that includes an additional convolutional layer in block 3, 4 and 5. The convolutional base of VGG16, VGG19 and ResNet-50 architecture has been used to extract features from processed mammography images. The models are freezed with ImageNet weights with a non-trainable layers [46] [47] and the top classification layer is excluded and replaced with a new classification layer.ResNet-50, a thinner and deeper architecture than VGG16 and VGG19, with the small size of convolutional filters in its architecture reduces the feature extraction time compared to VGG16/19 [48]. The pre-processed training image samples (MIAS/DDSM dataset) are supplied to each pre-trained model to extract the features from the given training samples. Each model generates feature vectors namely F1, F2 and F3. After feature vectors (F1, F2, and F3) are extracted, the features are concatenated and fed to EML classifiers to evaluate the classification score.

### D. Ensemble Machine Learning Classifiers

The concatenated features are supplied to the ensembled machine learning classifier model that includes five different classifiers namely Support Vector Machine, Decision Tree, Random Forest, K- Nearest Neighbor, Gaussian Naive Bayes. The maximum voting system is employed to predict the classification category and reduce the misclassification rate. Figure 5 shows the majority voting system for the prediction of breast mass class based on the ensemble machine classifier model.

### E. Trained Model deployment on RPI 3B

Before the model deployment is performed on RPI 3B, it is configured with the necessary configuration files and the frameworks necessary to execute the deep learning models. The pre-trained models VGG16.h5, VGG19.h5 and ResNet-50.h5 are deployed on RPI 3B (1.2GHz Quad-Core Broadcom BCM2837 64 bits CPU-1GB RAM) platform to carry out feature extraction from testing images. Since

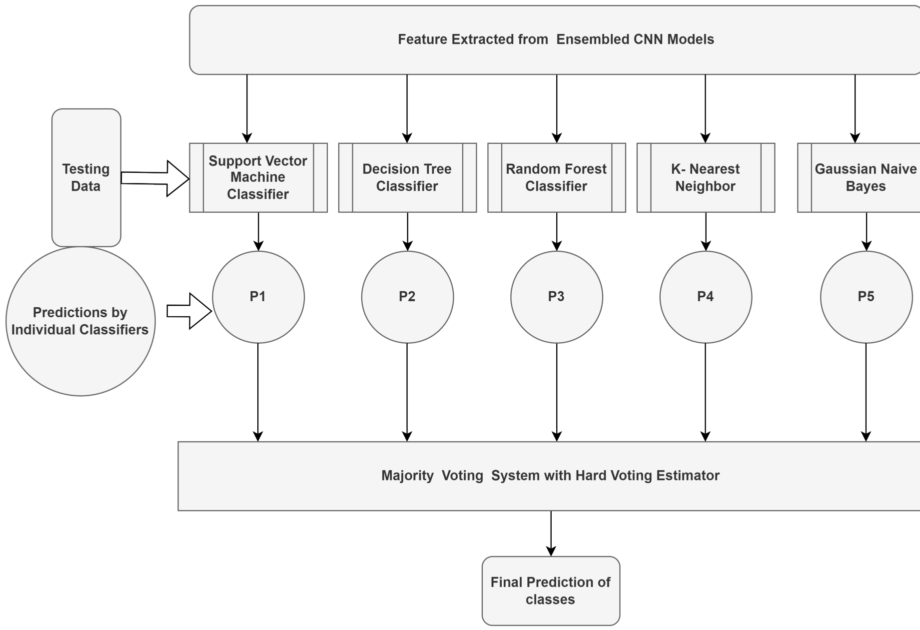


Figure 5. Majority Voting System

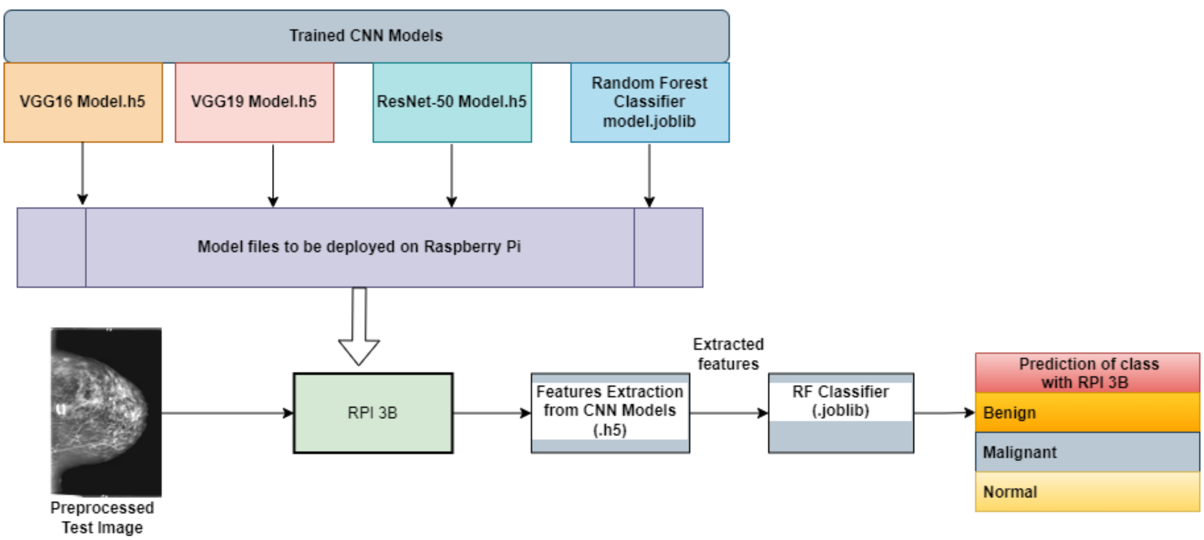


Figure 6. Workflow: Deployment of pre-trained models and RF classifier

Random Forest classier outperformed other classifiers in the classification of extracting features RF.joblib model is deployed to perform the classification. The lack of memory space and low computation capability of hardware platforms poses limitations in deploying big-size models. Hence, experiments have been made to deploy pre-trained models and RF classifier models for the testing phase using the RPI 3B platform. Figure 6 shows the workflow for deploying the trained Deep ensemble CNN model and trained RF classifier.

## 4. EXPERIMENT RESULTS

This section explains the experimental results of the proposed breast cancer detection system obtained with ensemble pre-trained CNN models and EML classifiers using two open-source datasets called as MIAS and DDSM. The results obtained without feature ensemble are also presented to demonstrate the high efficiency using the ensemble approach as compared to without feature ensemble. The machine learning performance measures like accuracy, F1 score, precision, AUC etc. are evaluated to know the effectiveness of the trained model. The hardware platform, Intel(R) Core(TM) i7-9750H CPU @ 2.60GHz has been used to implement the ensemble Deep CNN model to

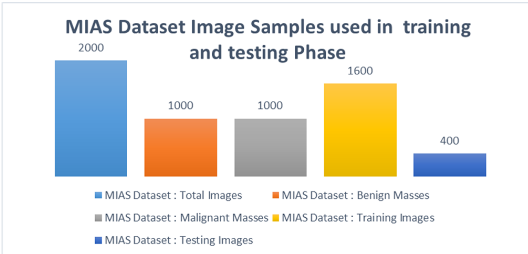


Figure 7. Training & Testing Image distribution [MIAS Dataset]

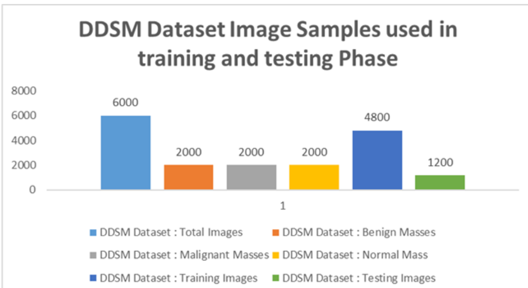


Figure 8. Training & Testing Image distribution [DDSM Dataset]

predict the type of breast mass in breast cancer detection process. The software codes are developed in python using frameworks such as TensorFlow, Keras and Scikit learn etc.

### *A. Datasets*

The MIAS and DDSM mammography images sample distribution used to train and test the proposed model is shown below in Figures 7 and 8 respectively. In order to strengthen the feature extraction process, MLO and CC views of mammography images have been utilized [49]. Out of total images, 80% samples for training and 20% samples for testing are used to obtain the trained models.

### *B. Image Preprocessing*

Image preprocessing is necessary to enhance the image contrast of low contrast mammography images. The mammography images of CC and MLO views are normalized before the application of CLAHE for local contrast enhancement. Figure 9, demonstrates the improvements in image contrast after the application of Histogram Equalization (HE) and CLAHE. Since CLAHE provides a better contrast over HE, the CLAHE-based mammography images are supplied to Deep CNNs.

### *C. Minimization of Loss function during training phase*

Prediction accuracy has been determined using Cross entropy (CE) loss function minimization during the training phase [50]. Binary and Categorical cross-entropy functions [51] are respectively used for MIAS and DDSM datasets are used to evaluate the cross-entropy score. With a sigmoid activation function, the cross-entropy function calculates the entropy score based on the difference between an actual label and predicted label probability distributions.

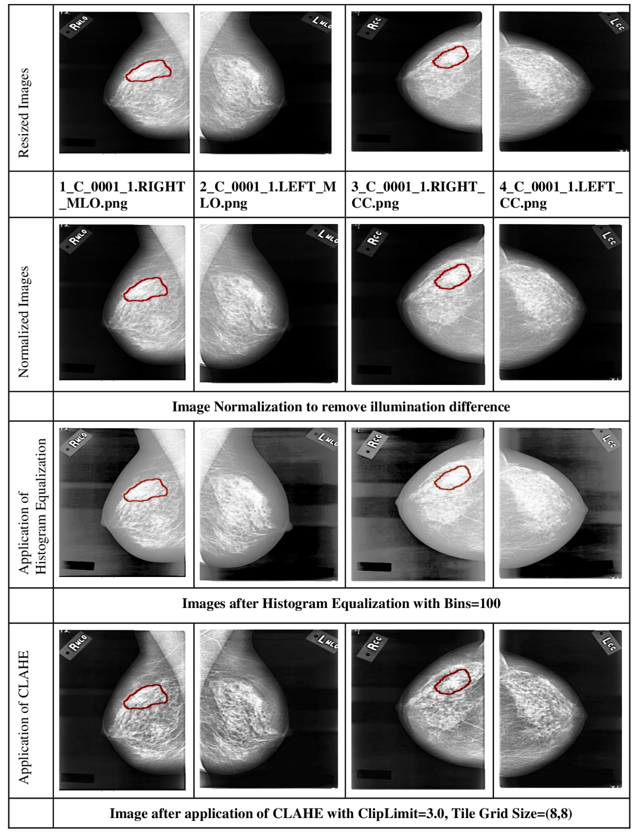


Figure 9. Pre-processing Steps applied for Mammography Images of MLO and CC View

The entropy score for MIAS dataset can be calculated from equation 4.

$$CE = (y_t Log(y_p) + (1 - y_t) * Log(1 - y_p)) \quad (4)$$

where, $y_t$=binary value for the given actual class label $y_p$=predicted probability

To perform the multiclass classification, CE is calculated by averaging the cross-entropy score calculated for each class with given training examples.

### *D. Experimental Results & Performance Metrics*

The experimental findings shown here compare the performance of pre-trained models with and without feature ensemble approaches using MIAS and DDSM Datasets. The results obtained with the feature ensemble approach are also compared with some of the most recent contributions made in the breast cancer detection system using deep learning techniques. To identify the type of breast mass in a mammography image, VGG16/VGG19/ResNet-50 models are used as feature extractors in stand-alone mode and the extracted features are classified further with Random

TABLE II. Performance matrices with VGG16/VGG19/ResNet-50 and RF Classifier

| Image Dataset | No. of Images | Total Images | Training Images (80%) | Testing Images (20%) | Pretrained Model Layer | Accuracy | Precision | Recall | F1-Score | AUC | Feature extraction time (minutes) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| MIAS Images | Cancer | 1000 | 1600 | 400 | Resnet-50 | 0.82 | 0.82 | 0.82 | 0.82 | 0.82 | 1.03 |
| | Benign | 1000 | | | VGG19 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 | 3.65 |
| | | | | | VGG-16 | 0.78 | 0.78 | 0.78 | 0.78 | 0.78 | 2.90 |
| DDSM Images | Normal | 2000 | 4800 | 1200 | Resnet-50 | 0.88 | 0.89 | 0.88 | 0.88 | 0.98 | 1.52 |
| | Cancer | 2000 | | | VGG19 | 0.92 | 0.93 | 0.92 | 0.92 | 0.98 | 2.02 |
| | Benign | 2000 | | | VGG-16 | 0.91 | 0.92 | 0.91 | 0.91 | 0.99 | 1,76 |

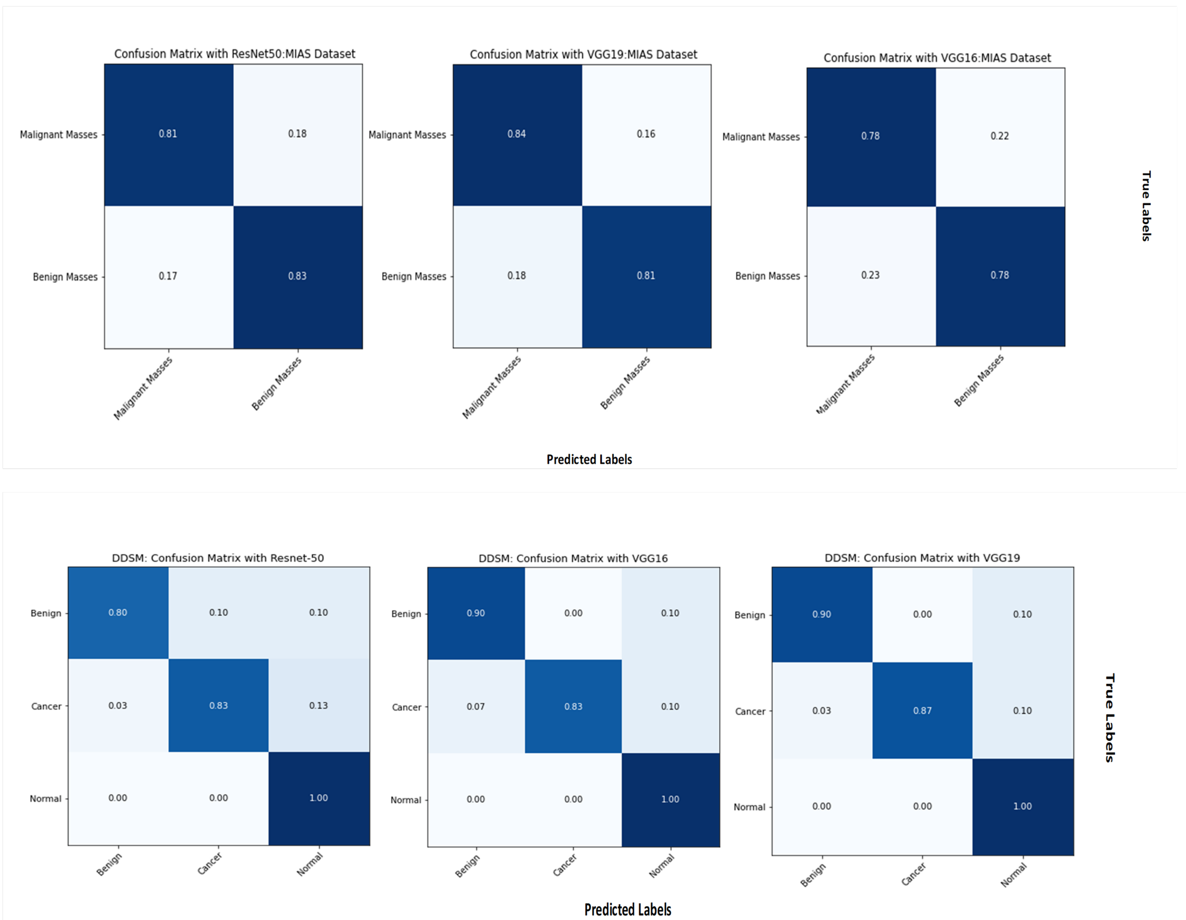


Figure 10. Confusion Matrix obtained with MIAS and DDSM Dataset

Forest, an accurate machine learning classifier with higher prediction accuracy [52][53], to evaluate the accuracy score. Table II shows the different performance matrices obtained with ResNet-50/VGG16/VGG19 with Random Forest classifier. Figure 10 shows the confusion matrices obtained with MIAS and DDSM datasets with this approach.

### *E. Simulation Results with feature ensemble approach*

The approach creates an ensemble of feature vectors extracted from VGG16, VGG19 and ResNet-50 pre-trained models by providing the base layers to form a CNN architecture in the feature extraction process from preprocessed mammography images. After features are concatenated, the EML (EML) classifier predicts the classification score. Table III describes the different performance measures obtained with the ensemble approach. Figure 11 shows the confusion matrix obtained with an ensemble approach for MIAS and DDSM datasets. Table IV describes our contribution with respect to some of the recent work carried out with Deep ensemble models using Mammography

TABLE III. Performance measures obtained with ensemble approach

| Image Data-set | No. of Images | Total Images | Train-ing Images (80%) | Test-ing Images (20%) | Feature ensemble using Pretrained Models | Feature extraction time for feature Concaten-ation (minutes) | EML Classifiers | Performance Matrices based on Majority Voting Systems | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Accuracy | Precision | Recall | F1-Score | AUC |
| MIAS Images | Cancer<br>Benign | 1000<br>1000 | 1600 | 400 | Resnet-50<br>VGG19<br>VGG-16 | 14.81 | RF<br>DT<br>SVM<br>GNB<br>KNN | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 |
| DDSM Images | Normal<br>Cancer<br>Benign | 2000<br>2000<br>2000 | 4800 | 1200 | Resnet-50<br>VGG19<br>VGG-16 | 41.53 | | 0.96 | 0.96 | 0.96 | 0.96 | 0.99 |

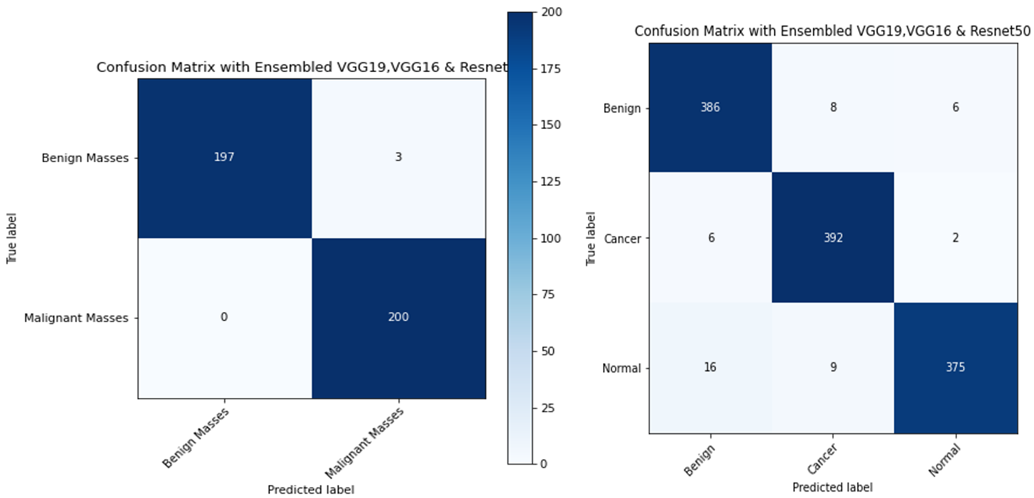


Figure 11. Confusion Matrix obtained using MIAS and DDSM Dataset: Feature ensemble approach

TABLE IV. Comparison of proposed work with some of the recent works

| Sr. No. | Breast Cancer Detection Methods | Year | Dataset | Accuracy |
|---|---|---|---|---|
| 1 | Hybrid Classifier(XGBoost and Random Forest) [54] | 2022 | MIAS<br>DDSM | 98.6%<br>94.3% |
| 2 | Feature extraction with Ensemble CNNs and Classification using Neural Network classifier [55] | 2020 | DDSM | 88% |
| 3 | Ensemble CNNs and SVM as [35] | 2022 | DDSM | 94% |
| 4 | Ensemble of LSTM and CNN in feature extraction and Random Forest and boosting techniques for classification [38] | 2021 | MIAS<br>DDSM | 95%<br>96% |
| 5 | Proposed Work | 2022 | MIAS<br>DDSM | 99%<br>96% |

image datasets. With a Deep CNN feature ensemble and an ensemble of machine learning classifiers, we achieved better prediction accuracy than the work contributed by authors [54] [55].

### *F. Deep CNN Model Deployment on RPI 3B*

Figure 12 depicts the deployment workflow of the trained mammography image classification model obtained with ensemble deep CNN and machine learning classifier on RPI 3B. As shown in Figure 12, RPI 3B is configured with 64-bit OS and SSH (Secured Socket Shell) file for wifi setup.

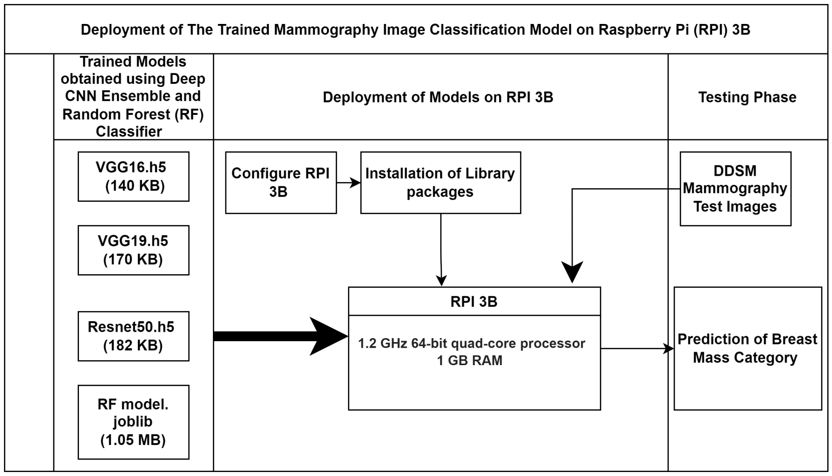


Figure 12. The hardware deployment of the Deep ensemble model and RF classifier

The VNC (Virtual Network Computing) is enabled to obtain remote screen-sharing access. The necessary library packages like Tensorflow and Sklearn are installed on the device to run the python script. The low computational capability of RPI 3B poses a limitation in carrying out training and testing phases both on it. The proposed methodology only deploys the trained ensemble Deep CNN models namely VGG16.h5 (140KB), VGG19.h5 (170 KB), ResNet50.h5 (182 KB) on RPI3B memory space. Testing of the deployed model is performed with DDSM test image. Three separate test feature vectors are obtained using .h5 model files.The feature vectors are concatenated and classified with Random forest classifier model file RF.joblib model (1.05 MB) to predict the class of breast mass from DDSM test image.

## 5. CONCLUSION AND FUTURE DIRECTIONS

The proposed model uses ensemble Deep CNN models, VGG16, VGG19 and ResNet-50 as feature extractors with the fixed feature extraction approach. The extracted features are categorized by an ensemble of machine learning classifiers by creating a classifier frame made with SVM, RF,DT and GNB with a majority voting system. Hence the implemented workflow highlights the model efficacy to improve the classification accuracy with a blend of deep ensemble models and EML classifiers compared to some of the recent works. However, the mammography image quality, distribution of images for the training and testing phase, selection of different pre-trained models as feature extractors, and classifier types with appropriate hyperparameters are pivotal in fixing the model accuracy. The proposed work also shows the direction to deploy the trained model on hardware embedded platforms like FPGA, RPI and Arduino etc. Although the breast cancer classification systems with deep ensemble models have shown their efficiencies in making the accurate prediction by extracting the important features from pre-processed mammography images, large feature vector size may cause constraints by demanding large memory space and feature extraction time. The different feature selection techniques can be explored further to select the most appropriate features and thereby reduce the feature vector size and extraction time. The hardware deployment of the trained model also creates a wide room for researchers to develop web-based CAD systems by integrating hardware platforms with web servers with more generalization ability and enhancing the existing decision-making capabilities to ease the medical fraternity. The availability of more standard and curated mammography datasets can also increase the potential of CNN in breast cancer detection and diagnosis.

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