ORIGINAL ARTICLE

Implementation of Improved U-Net and Optimized XGBoost-SVM Classifier for Early Detection of Masses and Microcalcifications in Breast

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Abstract

Purpose: In contemporary time, breast cancer has been extensively found among women at a global rate of 24.2% as of 2018. This exposes the significant and imperative need for detecting masses and micro calcifications in the breast to avoid death rates. The existing histopathological images have gained a golden standard considering they would afford reliable results. However, these images have been entangled with various complexities including insufficient image contrast, noise, and misdiagnosis. These pitfalls might negatively impact the detection rate for which automatic recognition has become vital. With the momentous evolvement of Machine Learning (ML) and Deep Learning (DL), various researchers have endeavoured to consider ML and DL for accomplishing this prediction. However, they need to improve in accuracy rate due to ineffective feature extraction, and most studies averted to consider segmentation. Hence, this study regards accomplishing a high classification and segmentation process.

Materials and Methods: The study proposes Modified Weight Updated Convolutional Block-U-Net (MWu-Conv-U-Net) to handle the image dimensions optimally. In this case, U-Net based model is regarded by improvising it with the inclusion of an additional convolutional layer in individual encoder-decoder. Further, the study proposes an Optimized Weight Updated eXtreme Gradient Boosting-Support Vector Machine (OWu-XGBoost-SVM) for determining the optimal gradient, which would eventually enhance the prediction rate.

Results: The overall performance is assessed through performance metrics to confirm its effectiveness in classifying and segmenting the Breast Cancer Histopathological (BACH) image dataset. Comparison is undertaken with conventional systems in accordance with metrics (recall, F1-score, precision, and accuracy). The results revealed the efficacy of the proposed system with 99% accuracy, 99% F1-score, 99% precision, and 99% recall.

Conclusion: High accuracy procured through the analysis reveals its efficacy and hence it could be applicable for real-time execution for assisting medical experts in early breast cancer prognosis.

Keywords: Deep Learning; Breast Cancer Histopathological Image; U-Net; eXtreme Gradient Boosting; Support Vector Machine.

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1. Introduction

Cancer is evolving as a leading reason for mortality rate. This disease is responsible for one out of six global demises. By 2018, nearly 18.1 million people were affected by cancer, with 9.6 million dying from this dreadful disease. This rate is probable to enhance in the forthcoming years. With the enduring epidemiological conversion where transmittable and infectious illnesses are being treated, and life expectancy seems to be enhancing, Non-Communicable Diseases (NCDs) like cancer are in the center stage. It has been claimed that, among all NCD mortality cases, 30% of the cases have been from cancer. In such a grim case, breast cancer must be emphasized as this disease is responsible for 2.1 million cases yearly [1]. This highlights the need for diagnosing breast cancer by identifying masses and microcalcifications from the breast. Typically, breast cancer seems to be diagnosed through several imaging methods like ultrasound, pathological tests, mammography, and thermography. Among these approaches, histopathology images have been regarded as a gold standard for patients who have undergone other scanning kinds to enhance the prediction rate, thereby affording reliable outcomes. Histopathological images from breast cancer-affected patients are gathered using suitable chemicals to tint the cell nucleus. Subsequently, other components are dyed with suitable chemicals for shading to emphasize several tissue structures and characteristics. After employing biopsy, diagnosis is undertaken by a pathologist evaluating the stained tissue through a microscope. Although such images are comprehensive, several complications, like meager contrast in the images, deficiency of recognition by the human eye, and noise, might lead to misdiagnosis. With the onset of ML- and DL-based models to overcome traditional Neural Networks (NNs) for resolving conventional issues, the researchers are concentrating on utilizing Computer-Aided Design (CAD) to enhance the test accuracy [2].

Accordingly, the research [3] has employed various algorithms for segmentation to extract 51-calcification features from the mammograms that include textual and morphologic features. eXtreme Gradient Boosting (XGBoost) has been adopted for classifying the microcalcifications. Subsequently, other ML algorithms have been compared, including K-Nearest Neighbour (K-NN), Random Decision Forest (RDF), Gradient Boosting Decision Tree (GBDT), DT, and AdaBoostM1 with XGBoost. It has been exposed that suggested system has revealed better accuracy in classifying the microcalcifications. Similarly, Inception Recurrent Residual CNN (IRRCNN) has been suggested to classify masses from the breast. Outcomes have exposed the better performance of IRRCNN. Experimental outcomes have been compared with conventional DL and ML algorithms about patch-based, patient-level, image-based, and image-level classification. The recommended model has afforded a better classification rate for Area under Curve (AUC), Receiver Operating Characteristics (ROC), accuracy, and sensitivity. Better performance has been attained [4]. To improvise the system performance of t-distributed Stochastic Neighbour Embedding (t-SNE) has been used for dimensionality reduction and exposing how CNNs classify histomorphologic information. A transparent and quantitative method has been developed for visualizing classification decisions before Softmax compression [5]. Through discretization of associations amongst classes on the t-SNE plot, it has been exposed that randomly sampled areas could be super-imposed, and their distribution could be used to render statistically driven classification. A DL-based algorithm has been used to accomplish efficient and quick classification guided by an attention mechanism [6].

The suggested methodology regards DenseNet advantages and utilizes the information of the feature map. Then, a dilated convolution has been suggested for generating a huge receptive area. Lastly, channel and spatial attention have been utilized to retrieve valuable visual features. Through the usage of 5-fold cross-validation, the accuracy rate has been exposed to be 96.47%. Evaluation has also been performed on various other datasets. Empirical outcomes have represented the better performance of the suggested model. As DL-based algorithms have evolved, a CNN model [7] has been considered for BACH image classification [8]. Recommended system of 3-parallel CNN branches encompassed three phases. The initial phase comprised of 3-parallel CNN with residual blocks. Subsequently, 3-parallel branches have been integrated to create feature fusion. Following this, fused features have been classified. Evaluation has been undertaken with a 97.14% prediction rate. It has been stated that future studies have to concentrate on enhancing networks with segmentation. By this, a segmentation process has been performed for which a breast cancer image has been introduced. Deep-analysis network settings have been suggested to segment images for determining ideal configurations that could be considered in an identical task. Overall outcomes have been assessed through pixel-wise metrics. Outcomes of SegNet, DeepLab, FCN, and U-Net have been exposed, and the results are 0.87, 0.86, 0.86, and 0.86 [9]. Although conventional studies have attempted to accomplish the detection of masses and microcalcifications from BACH image classification, most of the studies needed a prediction rate, and most studies have not focussed on the segmentation process. To evade this pitfall, the present research intends to perform the classification and segmentation of images from the BACH dataset using data mining algorithms.

The main contributions of this study involve optimal handling of the input image's dimensions using the proposed Modified Weight Updated Convolutional Block-U-Net (MWu-Conv-U-Net) for effective segmentation to localize the affected area. Further, the study intends to classify the BACH dataset images using the proposed Optimized Weight updated eXtreme Gradient Boosting-Support Vector Machine (OWu-XGBoost-SVM) for identifying the optimal gradient to enhance the prediction rate. Lastly, the study aims to evaluate the performance of the proposed system using the performance metrics, namely Intersection of Union (IoU), Hausdorff distance, dice coefficient, Recall, Precision, accuracy, and F-measure for confirming the effective performance.

1.1. Paper Organization

The paper is organized in the following way, with section II discussing the conventional works in BACH image segmentation and classification. In this section, practical problems are identified and emphasized. Subsequently, section III exposes the proposed system with proper flow, algorithms, and pseudo-code. Then, section IV explores the outcomes attained through implementing the proposed system. Finally, the overall study is concluded in section V with future directions.

1.2. Review of Existing Work

Existing researchers have endeavored to perform breast cancer histopathology image classification and segmentation for identifying masses and microcalcifications in the breast. The related problems are discussed in this section.

The study [10] has regarded the issues of classifying breast cancer through tissue images. DL-based algorithms have been used, and a two-phase CNN pipeline has been considered for resolving the hardware problems enforced by processing large images. The considered patch-wise network performs on minimum patches corresponding to the overall image and outputs only spatially fewer feature maps. The following network performs on the uppermost patch-wise network. The suggested network has been accountable for capturing local input features. Further, the research [11] has evaluated varied detection strategies for breast cancer by using imaging methods, data mining algorithms, and several other features. At first, the data has been pre-processed through the usage of window or cropping. Additionally, segmentation could be accomplished by the K-means algorithm. In the last stage, calcifications have been identified in bosom cancer. The suggested methodology has been executed in MATLAB for affording reliable performance.

In contrast, the image-wise network has learned to integrate these features for determining the association amongst neighboring patches for global inferences of image features, thereby retrieving confident scores of the class. The network has been trained through the ICIAR-2018 BACH dataset, exposing an accuracy rate of 95% on 4-class validation. The outcomes have confirmed that algorithms based on CNN have accomplished promising outcomes that performed better than conventional ML algorithms [12]. By this, the research [13] has suggested a method for classifying images from the BACH dataset encompassing assembling several compact CNNs. Initially, a hybrid-CNN model was designed that encompassed a global framework and local branch. Then, by embedding the suggested Squeeze Excitation Pruning (SEP) block into a hybrid framework, the significance of the channel could be learned, and repetitive channels could be eliminated. Finally, with varying data composition, a multi-model has been constructed and assembled for further enhancement of model generalization. The suggested scheme has accomplished promising outcomes in classifying the images of breast cancer.

Furthermore, these outcomes have created a basis to employ CNN in classifying histopathological images [14]. Accordingly, article [15] has suggested a BACH classification technique using hybrid CNN and Recurrent Deep Neural Network (RDNN). By the rich feature indications of image patches, the suggested method has regarded short and long-term correlations amongst patches by RNN. Empirical outcomes have exposed the better performance of the suggested system than the conventional algorithm with 91.3% accuracy. Further, the Ensemble of Multi-Scale CNN (EMS-Net) approach has been used to classify images of the BACH dataset into four main categories: normal, in situ, invasive, and benign. Analytical results have been assessed on BACH dataset that has exposed 91.75% accuracy in 5-fold cross-validation [16].

As varied approaches have been accessible, the study [17] has intended to afford assessment research with a descriptive comparison of traditional ML and DL algorithms to classify BACH images. A collection of features have been extracted using three feature extractors. Then, these features were fused to attain image representation which would serve as the input for training five traditional classifiers. For DL-based algorithms, Transfer Learning (TL) based approaches have been adapted to the renowned VGG-19 DL model. In this case, the pre-trained large-scale ImageNet has been fine-tuned in a blockwise manner on the considered images. Kernel Principal Component Analysis (KPCA) and PCA have been used for minimizing the handcrafted and deep features of the two-dimensional space, and later it has been intuitively visualized and compared. Outcomes have exposed that DL-based algorithms have performed better than traditional ML algorithms by exposing an accuracy range of 94.05%-98.13%. On the contrary, the accuracy range of DL algorithms has ranged between 85.65%-89.32%.

By considering the better performing ability of DL, the research [18] has aimed to design a better DL-based model to diagnose breast cancer specifically. Multi-path CNN has been used for identifying tumor-based sub-classes. Satisfactory outcomes have been obtained [19]. Nevertheless, without considering the better-performing capability of ML, the research has tried to utilize ensemble and ML-based algorithms for classifying image patches. The suggested system has accomplished better outcomes with 97.5% accuracy [20]. For producing suitable embedding for BACH images, the efficacy of triplet-loss optimization has been evaluated with the importance of integrating features from varied pre-trained models like ResNet, Inception-V3, and DenseNet. The recommended approach exposed a 92% prediction rate on the BACH dataset [21]. To address the issues of multiple classifications of BACH images, the study [22] has fine-tuned ResNet. The suggested system has accomplished 97.3% accuracy.

Furthermore, Multi-Scale Input and Multi-Feature Network (MSI-MFNet) framework has been suggested that could learn the complete texture and structural features of various scale tissues through the integration of hierarchical feature maps. Recommended system has determined the disease possibility on image and patch levels. The performance of the endorsed system has been evaluated, which has confirmed its better performance [23]. For improvising the performance, a DL-based framework has been suggested that could work better with less training data. Background and foreground features have been integrated, and image parts have been retrieved from dual mid-level pooling layers. The effectiveness of the suggested features in classifying BACH images using SVM has been assessed. Better performance has been exposed with 92.2% accuracy.

Furthermore, an enhanced classification approach called Deep Learning eXtreme Gradient Boosting (DLXGB) has been suggested for improvising the prediction rate. The accuracy rate has been exposed to be 97%. The suggested system has improved performance by integrating XGBoost and DL-based feature extraction to solve classification issues [24]. Additionally, the Multilevel Context and Uncertainty Awareness (MCUA) DL-based model has been recommended. The execution of the model has exposed a 98.11% accuracy rate. Empirical results have revealed that the proposed system has performed better than the conventional system [25]. For detecting regions with suitable invasive features, the PMNet approach has been suggested. The system has shown an F1-score rate of 88.9% [26].

Furthermore, BACH image segmentation has been focused in the study [27]. It encompassed a simple framework to merge model pathways with varying spatial scaling in the spatial association that could be readily considered in standard encoder and decoder networks. In addition, a context-wise classification process has been suggested. Findings have exposed the potential ability of the suggested system to enhance the diagnosis. Moreover, inspired by receptive field concepts, dilated CNNs have been endorsed to encode various contextual information. Finally, by the attention mechanism of the channel, feature attention and fusion models have been suggested for better filtering and integration of features. Likewise, the study [28] has considered the use of ultrasonography for evaluating 46 patients with microcalcifications that have been suspicious for malevolence determined at mammography. A twinkling artifact has been used for identifying microcalcifications. It has been concluded that the twinkling artifact has been valuable for the microcalcifications in ultrasound evaluations, permitting significant enhancement in identifying masses and microcalcifications from the breast.

Additionally, the study [29] has utilized a lightweight network which alleviates computational complexity. Compared to traditional models, the recommended system has enhanced the accuracy rate by exposing 87.02% [30]. The research [31] has integrated LEFM with U-Net, MA-net, DeepLabv3, and U-Net++. Besides, LEFM-Nets have been employed to segment adenocarcinoma. The suggested network has also been tested for F1-score and balanced accuracy. Outcomes have exposed a better performance of the recommended model. To address the issues associated with the integration of classification and localization, the study [32] has recommended a dual DL model, which has regarded two CNN model configurations, namely Recurrent CNN (RCNN) and Whole image based CNN (WCNN). Experimentations have exposed a better performance of the suggested system. The attained outcomes have exposed a better performance of the classifier with a 97.8% prediction rate and 94% segmentation rate [33].

1.3. Problem Identification

Significant problems that have been procured through the review of the above existing works have been summarized in this section.

- Existing studies have exposed different accuracy rates encompassing [10] that has exposed 95% accuracy while considering two stage CNN pipeline, [15] has exposed 91.3% accuracy while using hybrid CNN and RDNN, [16] has exposed 91.75% while utilizing EMS-Net, [20] has shown 97.5% accuracy while regarding ensemble and ML algorithms, [22] has exposed 97.3% accuracy with fine-tuned approach, [24] has revealed 92.2% accuracy with SVM and hybrid features. Therefore, though better outcomes have been exposed, the accuracy rate has to be enhanced.

- Most studies have only focused on classification and have yet to consider BACH image segmentation [10, 13, 15, 16, 20]. However, only a few researchers have regarded the segmentation process. Accordingly, the study [32] has used a dual DL model and has exposed 94% as localization accuracy, while the research [33] has considered 91.67% for watershed segmentation. Though the accuracy rate has been better in segmentation, it needs further improvement.

- To attain better outcomes, a deep pre-trained model like Inception V3 must be considered with the blockwise fine-tuning approach [17].

- Optimal feature extraction approaches must be exposed to enhance the classification performance [33].

2. Materials and Methods

The study endeavors to perform the segmentation and classification of images from the BACH dataset to identify masses and micro calcifications in the breast. Though traditional works have attempted to accomplish this, they need to improve about prediction rate. In addition, most of the conventional studies have disregarded the segmentation process. The present study aims to enhance the accuracy rate by focusing on classification and segmentation. To accomplish this, the BACH dataset is initially considered, and a sequence of processes is followed as depicted in Figure 1. After loading the Invasive and In situ images from the dataset, pre-processing is undertaken. In this phase, the images are resized as resizing permits models to train quickly. The pre-processed image is then fed into the train and test split. It is subsequently fed into the segmentation framework where the proposed Modified Weight Updated Convolutional U-Net (MWu-Conv-U-Net) performs segmentation. This is later fed into the trained model that outputs the segmented Region. The study has considered 80% of training and 20% of testing. Lastly, performance metrics are regarded to evaluate the efficacy of the proposed methodology.

In addition, the study concentrates on classifying the images from the BACH dataset based on a stepwise procedure, as shown in Figure 2. At first, the dataset is loaded, and pre-processing is undertaken. This is followed by deep feature extraction. Inception V3 architecture is considered to extract suitable and relevant features comprehensively.

Then, the dimensionality of the extracted features is reduced using the regarded PCA.This is fed into the train and test split. Finally, classification is performed using the proposed OWu-XGBoost-SVM to find the ideal gradient. The classification performance is assessed through performance metrics to prove the effectiveness of the proposed classifier.

The proposed algorithms are briefly discussed with suitable mathematical representations and algorithms in the forthcoming section.

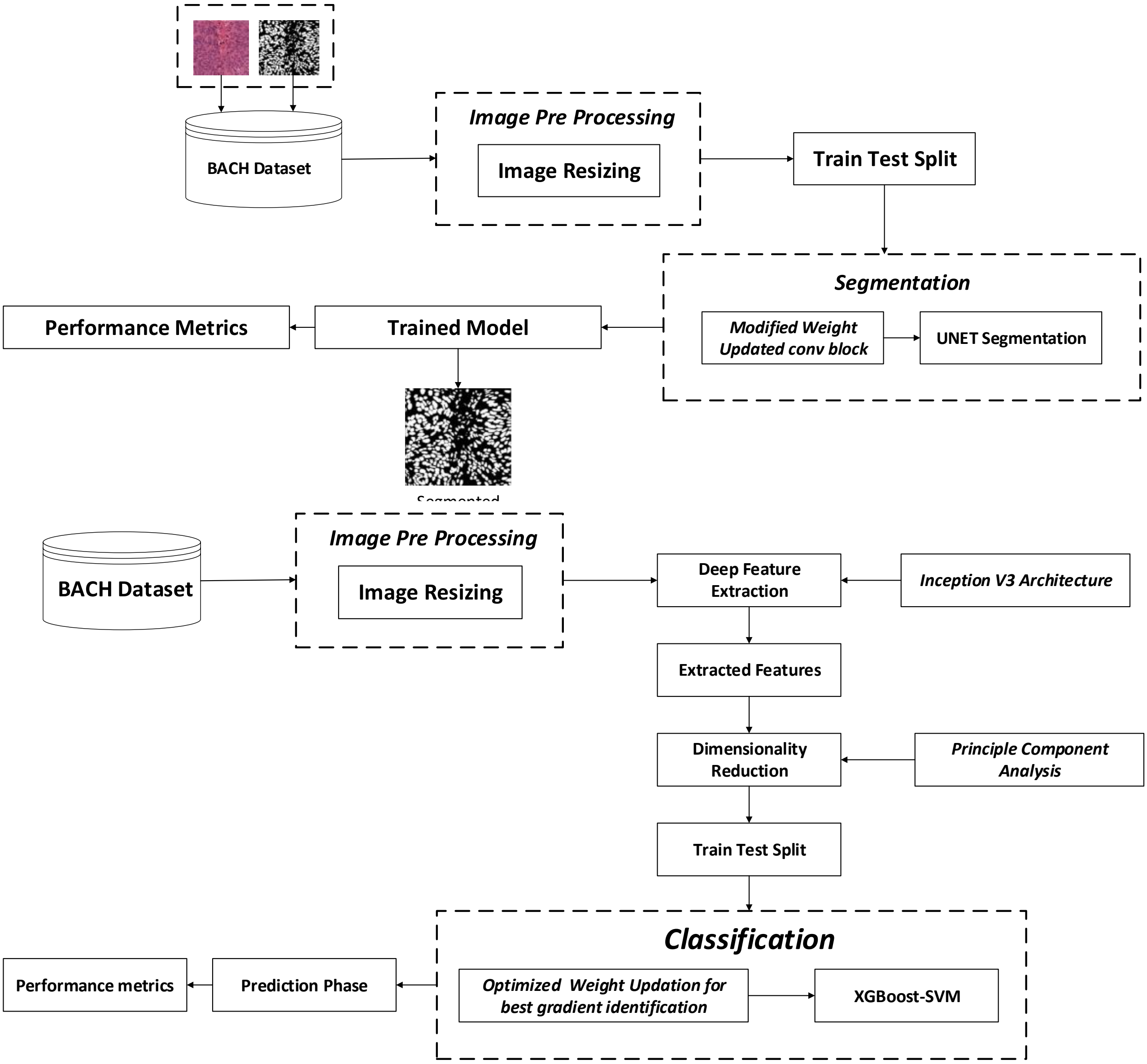


Figure 2. Overall view of the proposed classification process

2.1. Modified Weight Updated Convolutional U-Net (MWu-Conv-U-Net)-Segmentation

U-Net is generally a semantic-segmentation approach. This model possesses certain innate advantages to performing segmentation by permitting global location and context. Subsequently, it functions with fewer training samples, producing a better performance to accomplish segmentation. This study proposes a segmentation strategy for determining the Region of Interest (RoI) at the pixel level. The issue with the segmentation process is that RoI seems indistinguishable in the initial phases of breast cancer. To avert the drawback, the weights are increased in contracting and escalating the U-Net path with the addition of a convolutional module for establishing connections amongst the encoder-decoder pipeline.

The proposed system relies on the traditional U-Net model with the below enhancements,

i) Convolutional layers are included at an individual stage of the encoder structure, and similar convolution layers find applicability at individual decoder pathways. As a result, expansion, and contraction paths possess more Weight in comparison to U-Net.

ii) Total weights in the encoder-decoder module are enhanced from two to three.

iii) The enhanced model uses batch normalization before nonlinear operation.

Thus, for optimal handling of images with dimensions (128*128), U-Net based model is considered by enhancing it with the addition of an additional convolutional layer in individual encoder-decoder. The overall process is shown in Algorithm-I.

Algorithm-I: MWu-Conv-U-Net

TS: training sample
$TS = (A_1, A_2, A_3, A_4)$
Step-1: Input Samples = (Benign., Insightu, Invasive, Normal)
//Segmentation Images
lesion images = (Insightu, +Invasive)
Step-2: Train Images = [ ]
for each of Samples 1000 Training images:
Images of lesion images resize = (128 * 128)
Train_image[resized image]
$train_{images} = 200 * 128 * 128$
$train_{images}$ = plot with gray channel
end for
Step-3: //Segmentation Ground truth images
List of $images_{labels}$ = segmentation Groungtruth
Train Mask = [ ]
for each Samples train $_{images}$
Images of lesion images resize = (128 * 128)
Train_image[Mask image]
$train_{mask} = 200 * 128 * 128$
$train_{mask}$ = plot with gray channel
end for
Step-4: U − Net segmentation
Begin
U
− Net with 10,000 iterations selected from the 1000 training images
Initialize
Threshold = 0.5
for each image in train images(1000)
Step 5: Predict the segmented lesion area
fun (U − Net)
U − Net = (Upsampling, Merging, Downsampling)
Weight added to Upsampling
$upsampling_{weight}(train_{mask})$
Step-6: Use the weight − updated $conv_{block}$
Use the Weight added to Upsampling to optimize
threshold values that maximize the accuracy performance
Step-7: Model. predict → Segmented Region
end for
end
Step-8: return performance metrics
dice coefficient, Mean IoU, Hausdorff distance for background, lesion

2.2. Inception V3-Feature Extraction

Inception V3 is generally a DL model that relies on CNNs. This model encompasses asymmetrical and symmetrical building blocks wherein individual block encompasses several convolutions, max-pooling, average, dropouts, concats, and Fully Connected (FC) layers. Additionally, batch normalization finds applicability and employability to an input of the activation layer. In comparison, classification is accomplished by Softmax. Inception V3 model utilizes various methods to perform network optimization for better adaptation of the model. It possesses a deeper network than Inception V1 and Inception V2 models. However, its speed is not compromised. It is less expensive for computation and makes use of classifiers as regularizes. The overall architecture of Inception V3 is shown in Figure 3.

Moreover, the hyperparameters of Inception V3 are:

learning_rate: 0.001

batch_size: 32

epochs: 5

optimizer: 'Adam'

momentum: 0.9

2.3. Principal Component Analysis (PCA)-Dimensionality Reduction

The main idea behind PCA is that, with minimum loss of information and reliance on linear

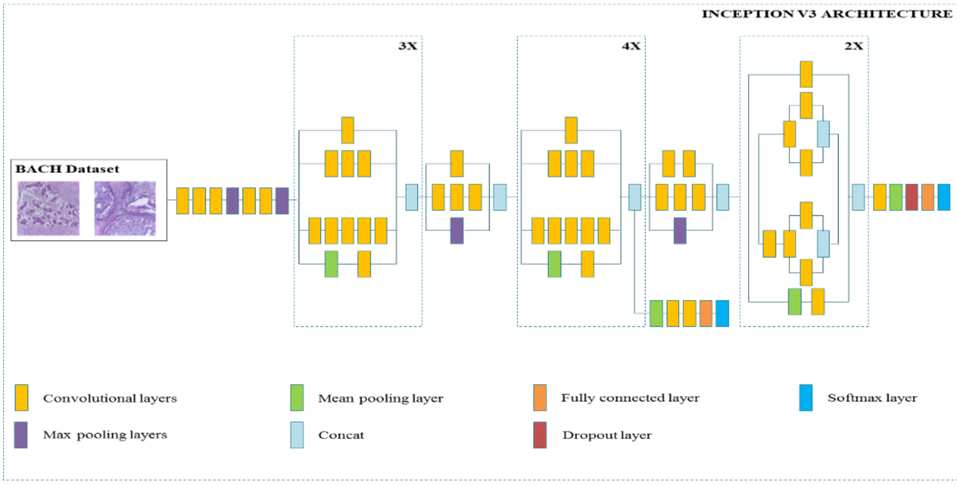


Figure 3. Inception V3 architecture

transformation, original data with multiple variants are modified with certain independent components. The actual nature of the sample could be explored by principal components that comprise their importance. PCA is considered in this study for dimensionality reduction as it can enhance model performance by eliminating related variables that do not contribute much to making decisions. Moreover, the algorithm time also lessens with minimum features. Thus, when input dimensions are large, using PCA for fastening the method is a practical option. Besides, PCA produces huge variance, which supports visualization.

Further, the reliance of PCA on linear algebra makes it computationally better. This algorithm also hastens other ML-based models, allowing fast convergence while training upon major components rather than actual datasets. The major phases of PCA are:

i) Standardizing primitive data to eliminate adverse effects instigated by varied dimensions.

Actual data are given by Equation 1:

$$H = (h_{ij})_{n*p} = (H_1, H_2, H_3, \dots \dots . H_P) \tag{1}$$

Standardization of the formula is given by Equation 2:

$$F_{ij} = \frac{h_{ij} - \bar{h}_j}{B_j}, \quad i = 1,2,3 \dots \dots . n; j = 1,2, \dots \dots ., p \tag{2}$$

Where,

$$\bar{h}_j = \sum_{i=1}^{n} \frac{h_{ij}}{n}, \quad B_j^2 = \frac{\sum_{i=1}^{n} (h_{ij} - \bar{h}_j)^2}{n-1} \tag{3}$$

The standardized matrix is depicted by Equation 4:

$$F = (f_{ij})_{n*p} = (F_1, F_2, \dots \dots . F_p) \tag{4}$$

Calculate Correlation Co-Efficient Matrix (CCM) as given by Equation 5:

$$CCM = \frac{1}{n-1} = F^t\, F \tag{5}$$

Where CCM denotes the $(n * n)$ symmetrical matrix, data within the diagonal=1, F^t represents the transposed matrix of F matrix.

ii) Compute Eigen-values and Eigen-vectors for CCM, wherein, Eigen-values (μ_i) are given by $|\mu E - CCM| = 0$, then sort (γ_i) by size $\mu_1 \geq \mu_2 \dots \dots \dots . \geq \mu_n \geq 0$.

The Eigen-vectors (FH_i) are procured by $(\mu E - CCM)H = 0$, $FH_i = (FH_{i1}, FH_{i2}, FH_{ip})^t$

iii) Determine the principal-components

The principal-component Contribution rate is depicted by Equation 6:

$$\alpha_i = \frac{\mu}{\sum_{i=1}^{p} \mu_i} \tag{6}$$

Further, the Cumulative Contribution (CuCo) of principal components (m) is given as per Equation 7:

$$CuCo_i = \frac{\sum_{i=1}^{m} \mu_i}{\sum_{i=1}^{p} \mu_i} \tag{7}$$

Generally, CuCo rates ($CuCo_i$≥85%) for principal components (m) are selected.

Determine the principal component as per Equation 8:

$$PCA_i = FH_{i1} \times F_1 + FH_{i2} \times F_2 + \cdots + FH_{ip} \times F_p \tag{8}$$

v) Discover comprehensive assessment function as given by Equation 9:

$$PCA = \frac{\mu_1 F_1 + \mu F_2 + \cdots + \mu_m F_m}{\mu_1 + \mu_2 + \ldots + \mu_m} \tag{9}$$

2.4. Optimized Weight Updated XGBoost-SVM (OWu-XGBoost-SVM)-Classification

The present study considers XGBoost in the classification process. It also possesses an in-built ability to handle missing values, and it encompasses several hyper-parameters that could be tuned. The hyperparameters of XGBoost as considered in this study are:

$params\ = \{$

$'learning\_rate'$: 0.1,

$'max\_depth'$: 100,

$'min\_child\_weight'$: 1,

$'subsample'$: 1,

$'colsample\_bytree'$: 1,

$'reg\_lambda'$: 1,

}

Whereas, SVM is productive in spaces with high dimensions. Therefore, the research proposes OWu-XGBoost-SVM, which can afford robust classification with the Optimized Weight Updated process. Through this process, the proposed system assists in optimal classification for enhancing the performance rate of diagnosing diseases with less False Positive (FP) rates. In contradiction to conventional gradient classification, the proposed system assigns Weight for individual SVM by relying on the loss function. After this, the gradient boosting algorithm calculates the loss function of the SVM classification. Then, the algorithm fits a computed loss function to its base classifiers. Correspondingly, the Weight Updated Gradient Boosting algorithm alters the weights by the loss function. Subsequently, the proposed algorithm determines the ideal gradient and updates the considered model for robust classification. The overall process is shown in Algorithm II.

3. Results and Discussions

The outcomes attained through the proposed system's execution are discussed in this section with dataset description, performance metrics, and comparative analysis results. Further, the environmental configuration encompassing all the relevant details related to hardware and software configuration considered for the present study are included in Table 1.

Table 1. Environmental Configuration

Hardware-Configuration	Software-Configuration
CPU-Intel Core i7-7700@2.80 GHz	Windows 10
GPU - GTX 1050	Python-3.7
RAM: 16 GB	Anaconda-Spyder

3.1. Dataset Description

This research uses the BACH dataset, which seems to be part of the ICIAR-2018 challenge to classify the H&E- breast cancer stained images. The dataset is encompassed in dual parts. The initial part of the dataset comprised four hundred microscopy image sections which are equally portioned into four classes (benign, invasive, in situ, and normal). On the contrary, the second part encompassed ten whole-slide images having high resolution wherein annotations are afforded for segmentation. The study has considered geometric transformation as the data augmentation method for increasing the samples to 1000. This study focuses on the first part of the dataset to validate the proposed method's performance [25]. A few sample images from the dataset are shown in Figure 4.

3.2. Performance Metrics

The significant metrics considered in this study for evaluating the performance of the proposed system are discussed in this section.

Algorithm-II: OWu-XGBoost-SVM

Step-1: Initialization
Training data from instance space (TS)
$S = \{(p_1, q_1), \ldots, (p_n, q_n)\}$ where $p_i \in P$ and $q_i \in Q = \{-1, +1\}$
Step-2: Initialize distribution $Dist_1(i) = \frac{1}{n}$
For ts=1….TS: do
Train a weak-learner $u_{ts}: A \rightarrow R$
Step 3: Find the weight δ_{ts} of u_{ts}
Step-4: Update distribution upon the training set
$Dist_{ts+1}(i) = \frac{Distri_{ts}(i)e^{-\delta_{ts}b_i u_{ts}(p_i)}}{E_{ts}}$
Wherein, N_{ts}-chosen normalization factor, $Dist_{ts+1}$-distribution
End for
Step-5: Overall score
$c(p) = \sum_{ts=0}^{TS} \delta_{ts} w_{ts}(p)$ and $N(p) = sign(c(p))$
//SVM classifier:
Input: Extracted Significant Features with medical data of the patie
Step-6: Begin
For each train data of a classification ‘ ’
Create an ′N ′ number of base SVM classifier
$N = (P1, P2, P3, \ldots PN)$
Step-7: Initialize weight ‘W ’for each base classifier
ϑ − −signifies the weight vector, −
→ P_i represents the data in classification , and b
− − is a bias.
$\vartheta . P_1 + b > 0$
$\vartheta . P_1 + b < 0$
Step 8: Determine the negative gradient
Fit a base classifier to a negative gradient using
$d = \varphi_1, \varphi_2 (\frac{2}{||\omega||})$
$\gamma i = sign(\omega * Pi + b) = sign(\sum_{i=1}^{n} \vartheta * \mu_i Pi + b)$
Step-9: Update weights ‘ W’ of base classifiers using
$w_i = \sum_{i=1}^{n} \emptyset_i(P)$
Step 10: Discover the best gradient descent step − size
$\xi = (ACi - \emptyset(P))^2$
Step-11: Update the model as a strong classifier
$\emptyset_i(P) = (P, (ACi - \rho(Pi))$
Strong classifier provides classification results‘ ’
Step-12: If results is $p == 0$ then
The patient is classified as normal, beneign
else results are $p = !\, 0$
The patient is classified as Invasive, Insitu
Endif
End for
End

i. Intersection over Union (IoU)

IoU calculates the prediction accuracy. Afforded with the ground truth, IoU is calculated through the overlap proportion area to union area, which is given by Equation 10. This could possess values between 0 and 1. With a maximum IoU value, the prediction rate is found to be better.

$$IoU = \frac{Over_{area}}{Un_{area}} \tag{10}$$

In Equation 10, Over_area represents the Overlap area, while, Un_area indicates the Union area.

ii. Dice coefficient

The dice coefficient, also termed DSC (Dice Similarity Coefficient), is static, which is used to gauge similarity among the considered samples and is given by Equation 11.

$$DSC = 2 * \frac{Pr * Re}{Pr + Re} \tag{11}$$

In Equation 11, *Pr* indicates Precision, and *Re* represents Recall.

iii. Hausdorff distance

It is claimed as the maximum variance amongst two different models calculated in a way wherein two points seem too far from the other. For example, provided with two point sets, $X = \{x_1, x_2, \ldots, x_n\}$, $Y = \{y_1, y_2, \ldots, y_m\}$, the Hausdorff distance within X, Y is given by Equation 12.

$$H(X, Y) = max(h(X, Y), h(Y, X)) \tag{12}$$

iv. Accuracy

It is stated as the computation of accurate overall classification and is represented by Equation 13.

$$Accuracy = \frac{Tru_N + Tru_P}{Tru_N + Tru_P + Fal_N + Fal_P} \tag{13}$$

v. Precision

It is defined as the computation of total accurate classification and is indicated by Equation 14.

$$Precision = \frac{Tru_P}{Tru_P + Fal_P} \tag{14}$$

As shown in Equation 13 and Equation 14, Tru_N-True Negative, Tru_P-True Positive, Fal_N-False Negative, Fal_P-False Positive.

vi. F-Measure

It is also called F1-score and could be stated as a harmonic mean of Pr and Re. It is computed by Equation 15.

$$F - measure = \frac{2 * Re * Pr}{Re + Pr} \tag{15}$$

vii. Recall

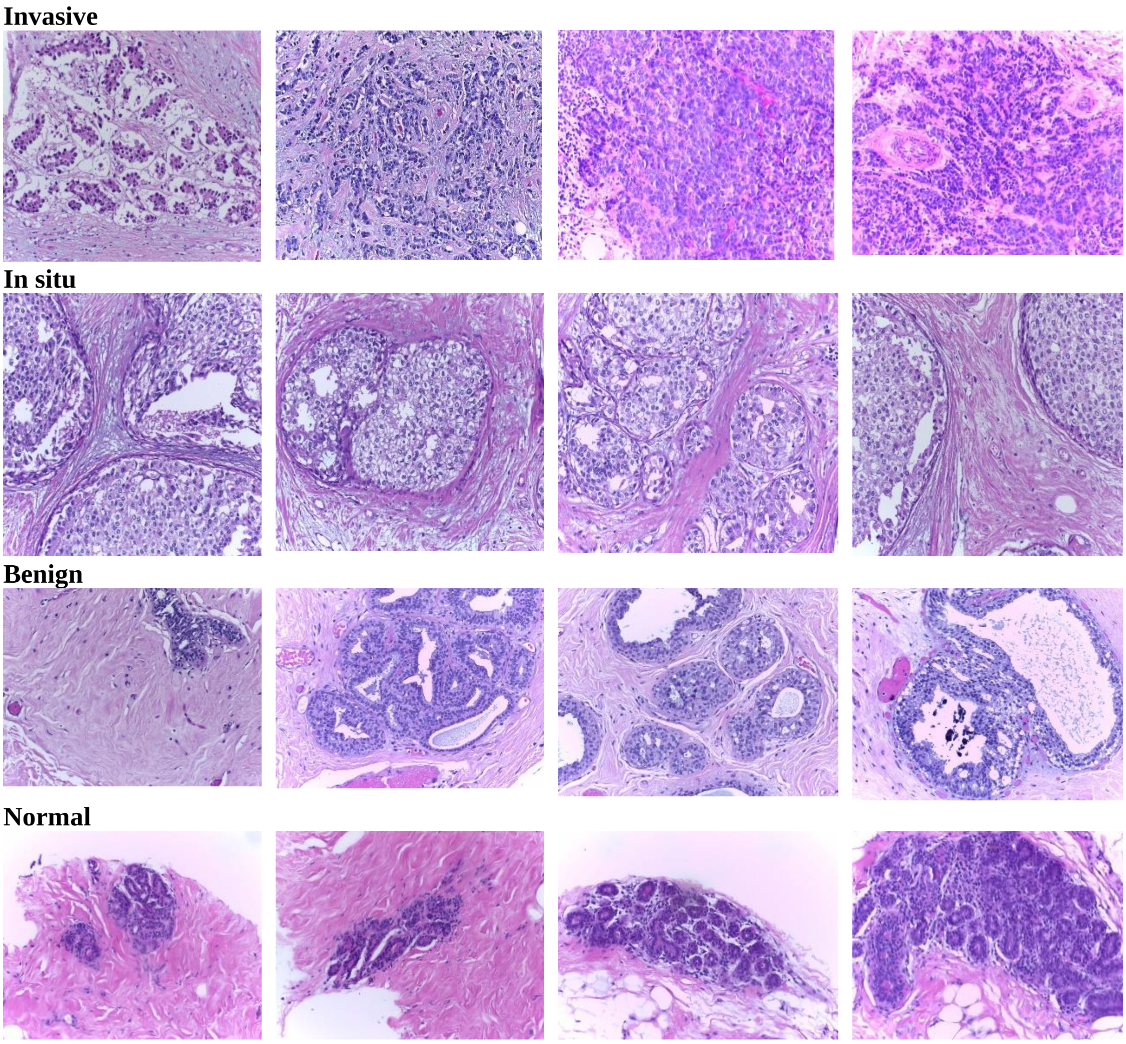


Figure 4. Sample images from the dataset

It represents the proportion of the Retrieved Image ($\mathrm{Retr_{img}}$) and Relevant Image ($\mathrm{Rel_{img}}$) to the proportion of the Relevant Image ($\mathrm{Rel_{img}}$). It is represented by Equation 16.

$$Recall = \frac{Rel_{img} \cap Retr_{img}}{Rel_{img}} \tag{16}$$

3.1. Experimental Results

This section discusses the results corresponding to the proposed system's execution. Accordingly, the results attained through the segmentation process are shown in Table 2.

Further, the performance evaluation of the segmentation process is undertaken about IoU, dice coefficient, and Hausdorff distance. Finally, the corresponding outcomes are exposed in Table 3, with its graphical representation in Figure 5.

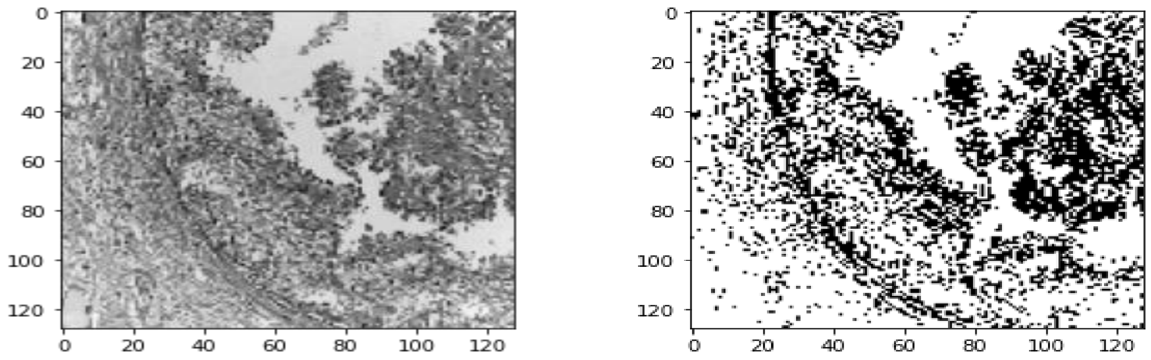
Table 3 and Figure 5, the IoU value of the proposed system is found to be 0.63673, while the dice coefficient is exposed to be 0.8529, the Hausdorff distance-background is revealed to be 5.12121, and the Hausdorff distance-lesion is found to be 5.12121. Furthermore, the classification performance of the proposed system has been exposed in Table 4.

From Table 4, classification outcomes about Precision for benign cases are exposed to be 1, while for normal, it is 0.95. Similarly, the recall and F1-score values for different classes are shown, and the average classification accuracy results for classifying all four classes are shown in Table 5.

Table 5 shows that the proposed system has exposed 0.99 as average accuracy, 0.99 as Precision, 0.99 as Recall, and 0.99 as Precision.

Table 2. Segmentation Results

Invasive	**Insitu**



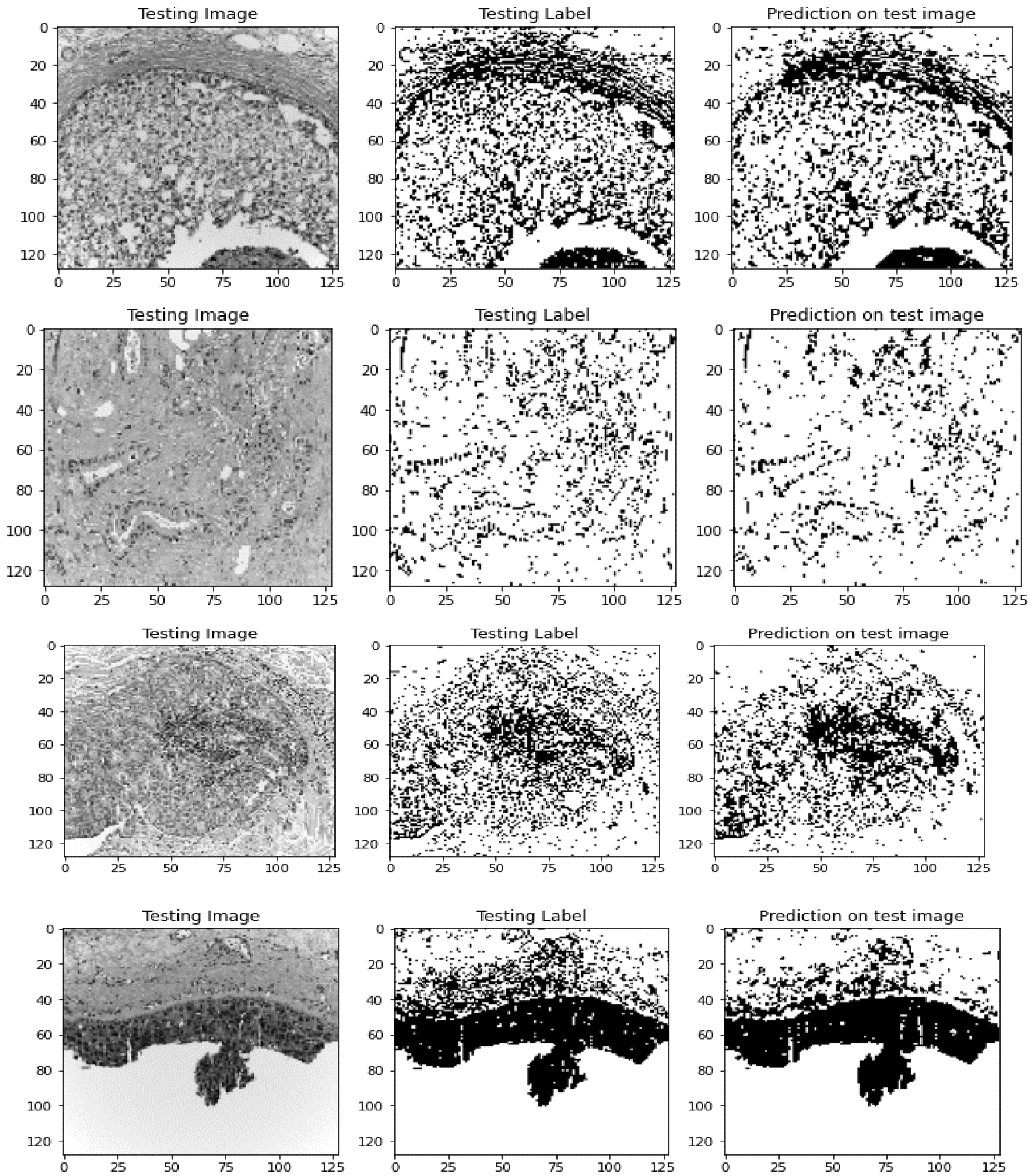


Table 3. Performance analysis of the segmentation process

Mean IoU		0.63673496
Dice Coefficient		0.852957
Hausdorff Distance	Hausdorff Distance - Background	5.121210802
	Hausdorff Distance- Lesion	5.121210802

Table 4. Classification Analysis

Classification Results	Precision	Recall	F1-score
0 (Benign)	1	1	1
1 (Insitu)	1	0.94	0.97
2 (Invasive)	1	1	1
3 (Normal)	0.95	1	0.98

Table 5. Performance analysis of classification

Average accuracy	Precision	Recall	F1-score
0.99	0.99	0.99	0.99

3.2. Comparative Results

The proposed system has been comparatively evaluated with conventional works to confirm its efficacy. The comparison has been undertaken with the current study [24], wherein fused features and SVM have been regarded as the existing system. The outcomes for classifying the four classes are shown in Table 6.

As shown in Table 6, the precision rate of the existing system for classifying normal cases is 0.9, while the precision rate of the proposed system to classify normal cases is 0.95. Similarly, the Recall and F1-score of the proposed system are higher than conventional methods in classifying the four classes. As accuracy is a significant metric for performance evaluation, a comparison has been undertaken about accuracy. In this case, various conventional algorithms have been regarded for evaluation, including DCNN+SVM, Ensemble of 3-DCNNs, Hybrid features + SVM, Hybrid features + MLP, Hybrid features + XGBoost, Hybrid features + RF, Pre-trained VGG-16 and Ensemble of Multi-Scale CNNs (EMS-Net). The analytical results are shown in Table 7.

Table 6. Comparative analysis of performance metrics [24]

	Existing				Proposed			
Class	**Normal**	**Benign**	**Insitu**	**Invasive**	**Normal**	**Benign**	**Insitu**	**Invasive**
Precision	0.9	0.91	0.94	0.93	0.95	1	1	1
Recall	0.9	0.89	0.94	0.96	1	1	0.94	1
F1-score	0.9	0.9	0.93	0.94	0.98	1	0.97	1

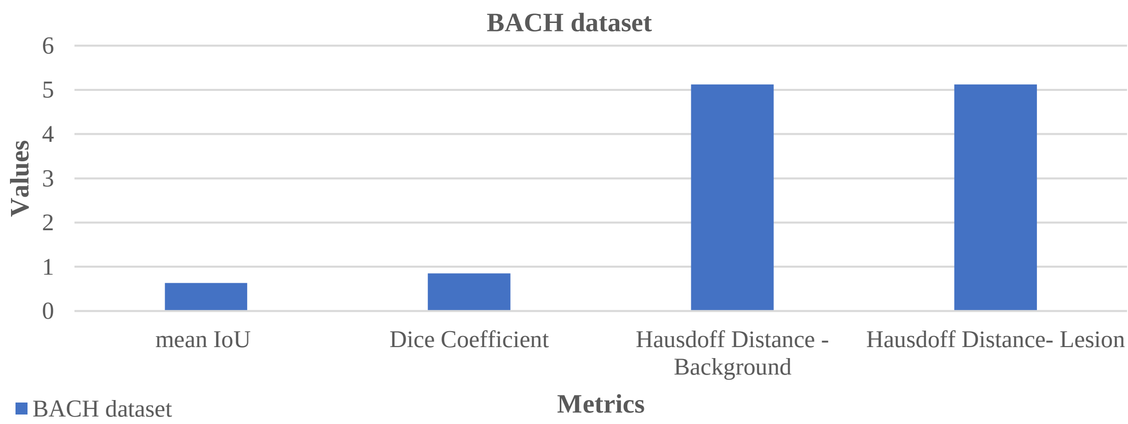


Figure 5. Segmentation Analysis

Table 7. Comparative analysis of accuracy [24]

Methods	Accuracy (%)
DCNN+SVM,	77.8
Pre-trained VGG-16,	83
Ensemble of three DCNNs	87
EMS-Net	91.7
Our hybrid features + SVM	92.2
Our hybrid features + MLP	85.2
Our hybrid features + RF	80.2
Our hybrid features + XGBoost	82.7
Proposed system	**99**

As exposed in Table 7, the accuracy rate of DCNN+SVM is exposed to be 77.8%, while EMS-Net has explored 91.7%, and Hybrid features + SVM has revealed 92.2%. In comparison, the proposed system has exposed high accuracy of 99% than conventional algorithms like Hybrid features + MLP, Hybrid features + RF, and Hybrid features + XGBoost. Furthermore, the performance of the proposed system has been evaluated by comparison with the conventional system [34] about accuracy that comprised of various existing neural networks of ResNeXt129 and MobileNetV2. Attained outcomes are shown in Figure 6.

From Figure 6, for baseline teacher training, the results of existing ResNeXt129 has exposed to be 75%, while MobileNetV2 has exposed 60.71%, whereas, for Normal KD, the existing ResNeXt129 has been exposed to be 60.71%. In comparison, MobileNetV2 has exposed 60.71%. For Reverse KD, the existing ResNeXt129 has been exposed to 65.58%, while MobileNetV2 has been exposed to 65.58%. On the contrary, the existing approach for bilateral KD has shown high performance at a rate of 96.3%. However, the proposed model has exposed high accuracy rate of 99% than conventional algorithms. Further, the comparison has been undertaken with the existing system [10] comprised of a two-stage CNN pipeline. The attained results are exposed in Table 8 with its equivalent graphical representation in Figure 7.

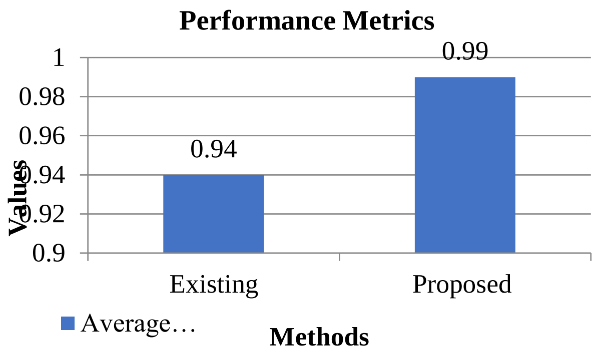


Figure 7. Analysis of average accuracy [10]

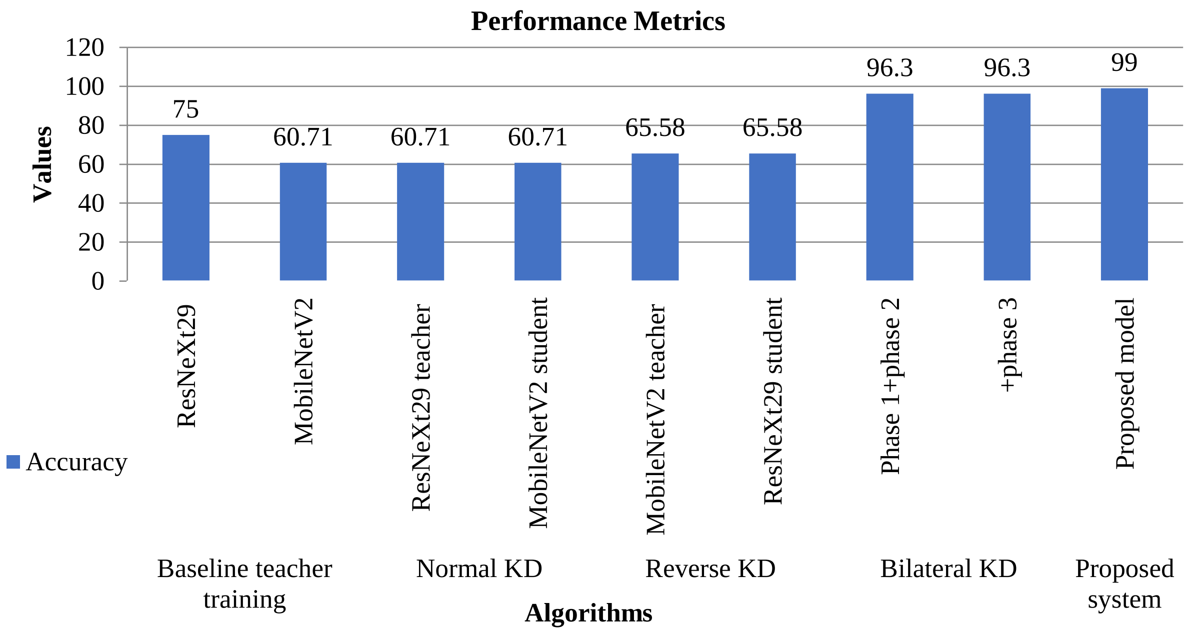


Figure 6. Analysis of accuracy [34]

Table 8. Comparative analysis results [10]

	Existing	Proposed
Average accuracy	**0.94**	**0.99**

Table 9. Analysis with regard to accuracy [35]

Backbones or methods	Accuracy
Inception-ResNet-v2	0.76
VGG16	0.79
Custom CNN (Capsule Network)	0.72
Densenet-161	0.83
ResNeXt50	0.81
VGG16	0.83
Resnet18	0.78
Resnet18 + ECA + MPN-COV	0.85
Proposed	**0.99**

From Table 8 and Figure 7, it has been exposed that the existing method has shown 0.94 as accuracy, while the proposed model has exposed 0.99 as accuracy. In addition, analysis has been undertaken with conventional study in accordance with accuracy rate and the respective outcomes are tabulated in Table 9 with its equivalent graphical depiction in Figure 8.

From Table 9 and Figure 8, it has been found that the existing models like Resnet18 + ECA + MPN-COV has shown better accuracy of 0.85, while, other algorithms like Densenet-161 have exposed 0.83, ResNeXt50 has shown 0.81. However, the proposed system has performed superior with 0.99 as accuracy rate. To consider the convolutional module with the U-Net, the segmentation process seems effective, which is confirmed through analysis. Further, the less expensive nature of Inception V3 about computation, the huge variance nature of PCA, and the ability to accomplish better classification with the weight-updated process have made the proposed system attain better outcomes that are confirmed through the analytical outcomes. Moreover, Inception V3 is an enhanced version of prior Inception models. It is considered with the intention of enhancing the accuracy rate while minimizing computational complexity. Certain merits of Inception V3 over other networks include enhanced accuracy: the Inception V3 model possesses the ability to accomplish better accuracy with a range of feature extraction. Following this, it is better performing in accordance with computational complexity: the Inception V3 accomplishes this by inclusive of several methodologies like factorized convolutions that significantly minimize the computational needs and overall parameters. Subsequently, Inception V3 model is generalizable that comprises varied parallel paths, permitting the model for capturing information at varied resolutions and scales resulting in optimal generalization and enhanced feature extraction. Overall, the Inception V3 model is more efficient than other networks with an optimal balance of accuracy rate. This has also contributed to the better performance of the proposed model. Thus, from the comparative analysis with three conventional studies [10, 24, 34], it has been exposed that the proposed system has shown outstanding performance than the conventional system.

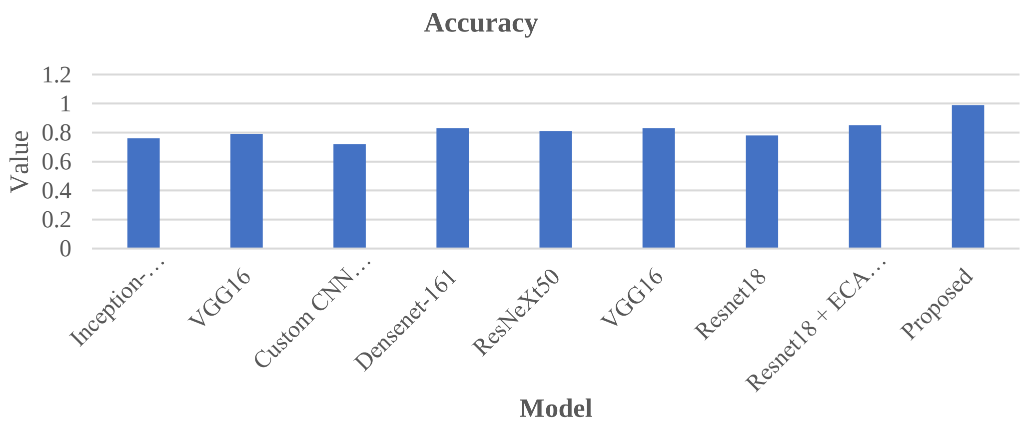


Figure 8. Comparative analysis with regard to accuracy [35]

4. Conclusion

The research intended to detect masses and microcalcifications in the breast by segmenting and classifying BACH dataset images. To achieve this, the study used MWu-Conv-U-Net for segmentation and OWu-XGBoost-SVM for classification. Inception V3 was considered for feature extraction and PCA for dimensionality reduction in the classification process. The study considered IoU, Hausdorff distance, and dice coefficient as metrics for analyzing segmentation outcomes. At the same time, Recall, Precision, accuracy, and F-measure were regarded as performance metrics to evaluate the classification results. From analysis, the segmentation results were exposed to be 0.636734 as IoU value, 0.85295 as dice coefficient, and 5.1212 as Hausdorff distance. On the contrary, the classification outcomes of the proposed system were explored to be 0.99 as the accuracy rate. Further, to confirm the effective performance of the proposed system over conventional studies, three recent types of research were considered. The analytical outcomes explored the outstanding performance of the proposed system over than existing system in all three comparisons with 99% accuracy for detecting the four microcalcification classes (normal, benign, invasive, and in situ) from the BACH dataset. The segmentation process can be tested in the future with different conventional studies so as to identify microcalcifications in the breast.

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