ISSN: 0974-5823 Vol. 6 (Special Issue, Nov.-Dec. 2021)

International Journal of Mechanical Engineering

A Hybrid Deep Learning Approach for Breast Cancer Detection Using VGG-19 and Support Vector Machine

Mr. K. VigneshKumar[1], Dr. N. Sumathi[2]

[1]Research Scholar (PhD) / Department of Computer Science,

Sri Ramakrishna College of Arts & Science, Coimbatore,

[2]Head / Department of Information Technology,

Sri Ramakrishna College of Arts & Science, Coimbatore,

Abstract: Breast cancer has been a major challenge in the arena of health sector as reports from literature quote a 20% of women population being affected by this fatal disease on a global scale and nearly 32% of it being shared by Indian population. However, if detected and treated at an early stage, there could be a massive reduction in the fatality rates. In recent time, medical health sector has achieved great milestones in detection and treatment of various disorders, thanks to the rapid pace of research and advancements in various fields like imaging modalities, segmentation and 3D processing techniques and availability of a powerful set of classifiers and predictors given a data set. Machine learning models have recently evolved as a powerful tool providing solutions to a number of such research challenges that involve intelligence, learning decision making with pinpoint accuracy. This work proposes a deep convolution neural network model -VGG-19 to attain high accuracy and precision in the cancer detection process. The computational complexity is effectively reduced by the proposed model over conventional methods the proposed deep learning model is able to perform both preprocessing and feature selection. Along with a powerful classifier inbuilt, an SVM is integrated into the proposed model to enhance the detection rate. The work has been carried out using the Wisconsin Breast Cancer Dataset (WBCD)which has an expansive data set of mammographic images. Performance metrics have been validated and justified by comparing against recent methods in terms of metrics like detection accuracy, precision, recall.

Keywords: Breast cancer detection, Deep Learning, Detection accuracy, Support Vector Machine, Mammograms.

1. INTRODUCTION

Cancer is one of the serious illnesses in which abnormal cells infects a normal cell and convert them into cancer cells. Among different types of cancer, specifically to women breast cancer is one of the harmful diseases which are either invasive or non-invasive. Invasive cancer will start in one place and spread to other parts or organs. In the case of non-invasive, the cancer is static and will not move to other parts. Most of the breast cancers are invasive which will appear in milk ducts and glands. Starting from the breast these types of cancers move to other organs through the bloodstream. Different types of breast cancers are listed so far and as per the report from the World Health Organization report 2.3 million women were diagnosed with breast cancer and 685 000 deaths globally in 2020. In the past 5 years, total 7.8 million women were diagnosed. Figure 1 depicts a sample illustration for normal and cancerous mammogram images.

Figure 1 Mammograms of breast

Breast cancers are mainly categorized into seven types as follows.

- Invasive ductal carcinoma [1] - Abnormal cancer cells that began forming in the milk ducts have spread beyond the ducts into other parts of the breast tissue.

- Invasive lobular carcinoma[2] - Cancer that began in the milk-producing lobules of the breast has broken through the lining of the lobule and spread into surrounding breast tissue.
- Paget’s disease of the nipple [3] - Cancer cells grow in the nipple or the areola.
- Inflammatory breast cancer [4] - Rare and aggressive form of invasive breast cancer that affects the blood vessels in the skin and/or lymphatic vessels of the breast.
- Phyllodes tumors of the breast [5] - Tumors develop in the breast’s connective tissue or stroma
- Locally advanced breast cancer [6] - Cancer that is large or has spread beyond the breast to other nearby areas such as the skin, chest wall or muscle and may have extensive local lymph node involvement.
- Metastatic breast cancer[7] - Cancer that has spread to more distant parts of the body such as the bones, liver, or lungs.

In order to diagnose cancers ultrasound, mammogram, magnetic resonance imaging (MRI) is used. The images are classified to identify the cancer status. Sometimes through biopsy, the cancer status is identified. However, the simplest and quick way to know the status of cancer is image-based analysis. Based on the results of image analysis, further tissue tests can be made. In image processing, machine learning plays a major and various machine learning-based breast cancer detection applications are introduced. The images acquired from the above-mentioned methods are classified using machine learning. Support vector machine [8], linear regression, Naïve Bayes [9], decision trees [10], k-nearest neighbor [11] are some of the familiar supervised machine learning models used so far for the detection of breast cancers. Neural networks [12] [13], independent component analysis, principal component analysis [14]are some of the familiar unsupervised machine learning algorithms used for breast cancer detection.

However, machine learning models provide better results if the data is small. In the case of large data, the accuracy of the machine learning approaches is reduced which redirects the research to focus on other learning techniques. There are few hybrid approaches which include multiple techniques to detect, segment, and classify the cancers from an image. But the results are not accurate due to the variation of the masses in the surrounding tissues. The texture, size, location, and shape of the masses make the detection into a complex process. Since the irregularities in abnormal tissues, low contrast boundaries might produce false positive and false negative results which mislead the diagnosis process. The semi-automatic feature extraction techniques in the hybrid approaches extract features based on prior knowledge but these systems cannot able to deal with the complex variations in shape and texture. Manual feature extraction is a quite time-consuming process and it is not advisable in the digital era. As an alternative to conventional segmentation, few studies utilized deep learning models as an alternate to extract and classify the features from raw input data.

Deep learning algorithms gain more attention the recent days due to their efficient and accurate performances. Basically, it is a type of artificial neural network which acquires features automatically and produces desired outcomes with minimum computation cost compared to machine learning algorithms. Deep learning architectures like deep neural networks [15], deep belief networks, convolutional neural networks [16], and recurrent neural networks are widely used in video processing, audio processing, natural language processing, medical image analysis etc., Among the different deep learning techniques, convolutional neural network (CNN) [17] is widely used as it is simple and easy to implement, extracts feature without any manual intervention, and classify the features through its fully connected network. Various context images and its features can be efficiently processed through CNN and due to this reason; it is widely adopted in healthcare applications. Various CNN models are evolved to explore the merits of deep convolutional neural network in the mass detection process.

In this research work a deep convolutional neural network model;VGG-19 is used to detect breast cancer from mammograms as early-stage detection. The presence of breast cancer is detected using the proposed deep learning technique so that fatality can be reduced by providing proper medication in the early stage. The contribution of this research work is summarized as follows.

- We have presented a deep convolutional neural network to detect breast cancers from mammograms.
- VGG-19 deep convolutional neural network model is used as a detection model along with a support vector machine to classify the status of cancer into malignant or normal.
- Presented an intense analysis using benchmark data sets such as Wisconsin Breast Cancer Dataset (WBCD) in terms of accuracy, precision, specificity, sensitivity, error rate, and processing time.

The remaining part of the research work is structured as follows. A brief literature analysis is presented in section 2;proposed breast cancer detection model is presented in section 3. In section 4, the result and discussion are presented and finally section 5 the observations are concluded.

2. RELATED WORKS

A brief literature analysis of existing breast cancer detection models is presented in this section. The methodologies, feature merits, and demerits are analyzed to frame the research motivation. Machine learning models are the early stage detection models evolved for breast cancer detection. The K-nearest neighbor-based detection model reported in [18] [19] measures the distance among data to detect the abnormalities in breast cancer detection. These distance measures are efficiently used along with a linear support vector classifier for feature selection to attain better detection performance. In order to process essential features and reduce the computational complexity of K-NN and decision tree algorithms, principal component analysis is incorporated in [20] and selects optimal features for classification. The Bayesian approach is another familiar model in machine learning which is employed in [21] to detect breast cancers. Three classifier models are employed such as tree augmented Naïve Bayes, Bayesian network, and conventional Naïve Bayes approach as a comparative analysis. Among these three Bayesian networks outperforms than other algorithms in the breast cancer detection process.

A modified k-means algorithm reported in [22] for breast cancer detection improves the classification accuracy of support vector machine [23]. The clustering algorithm generates a better training dataset which reduces the computation time of classifiers in the training process which further improves the classification results. K-means algorithm is combined with fuzzy c-means in [24] to attain better clustering accuracy in the breast cancer classification process. The feature parameters of k-means are combined with fuzziness value and termination criteria to obtain better outcomes in the breast cancer detection process. A similar fuzzy-based hybrid model reported in [25] combines fuzzy with rough set theory to detect the early-stage breast cancers from mammograms. Considering diverse attributes from data a strong decision is obtained based on the fuzzy rules. The presented approach identifies different types of malignant and benign stage cancers with minimum computation cost compared to the conventional approach.

A support vector machine-based ensemble learning algorithm is reported in [26] to enhance the diagnosis accuracy and reduce the variations in the diagnosis results. Research work employed twelve different vector machines which are obtained based on receiver operating characteristic curves and hybridization process. From the intense analysis, adaptive boosting and bagging classification tree models are identified as better models based on the high detection accuracy and minimum variance compared to other models. In literature [27] comparative analysis of logistic regression, multilayer perception, and support vector machine with stochastic gradient descent optimization is presented for breast cancer detection. The hard and soft voting procedure considers the majority voting mechanism, average probability, maximum and minimum probability in the detection process. Compared to soft voting the hard-voting procedure attains maximum detection accuracy in the cancer detection process. In [28] multilayer perception network is combined with principal component analysis for breast cancer detection. Initially, the data dimensions are reduced using PCA and optimal features are selected for further classification process. The MLP model extracts the data characteristics and explores the data as attributes which are used in the classification process. Similarly, literature [29] measures the performance of classification techniques like linear discriminant analysis, probabilistic neural network, and k-nearest neighbor for breast cancer detection. Before classification, principal component analysis is used to select the important feature index to improve the classification accuracy and reduce the computation complexity.

An improved random forest model for breast cancer detection reported in [30] introduces rule extraction to overcome the limitations in the conventional random forest approach. The decision tree models are generated using random forest and decision rules are obtained to train the tree network. From the generated rules, an optimal rule is predicted using a multi-objective evolutionary algorithm to obtain a better tradeoff between interpretability and accuracy. An integrated Bayesian classifier model for breast cancer detection reported in [31] deals with discrete and continuous features in the detection process. Different feature subsets are provided to the hybrid Bayesian classifier and AUC metrics are observed as a fitness index. The near-optimal feature subset which provides better results is identified using a genetic algorithm so that with minimum convergence maximum accuracy is attained in the hybrid breast cancer detection model.

Various optimization models are evolved to select the optimal features from mammograms in the cancer detection process. The whale optimization algorithm-based breast cancer detection model presented in [32] selects the optimal features to improve the classification accuracy of an extremely randomized tree classifier. By selecting the optimal features, the feature dimensionality is reduced which increases the detection accuracy compared to conventional approaches. The artificial bee colony optimization and integrated artificial immune system-based detection model reported in [33] selects the optimal features and classifies the features using an artificial neural network. The hybrid approach utilizes the feature merits of simulated annealing to enhance the local search process and attains better performance than existing optimization algorithms like genetic algorithms. The hybrid optimization model for breast cancer detection reported in [34] incorporates artificial bee colony optimization and enhanced monarchy butterfly optimization algorithms. The search space exploitation rate and search diversification possibility of an artificial bee colony are enhanced using butterfly optimization to attain better accuracy in the detection process. A firefly optimization algorithm reported in [35] obtains a better and accurate solution in breast cancer detection through its composite attraction characteristics. The probability of generating an optimal solution is increased using the composite attraction properties which enhance the recognition accuracy.

The above literature analysis clearly describes that machine learning models are widely used in the breast cancer detection process. Specifically, K-NN and support vector machine algorithms are widely used as a single model or a hybrid model. However, these models provide better results for the minimum dataset. Since K-NN depends on the k-value and its prediction accuracy is less when the data size increases. In case of noisy or large datasets the performance of the support vector machine reduces. However, for optimal feature selection, conventional and hybrid optimization models are reported in numerous research works. The artificial bee colony is one of the familiar models employed in multiple works. However, it requires a high number of objective functions to obtain the classification results. To overcome the observed limitations deep learning-based breast cancer detection is presented in this research work in the following section.

3. PROPOSED WORK

The proposed breast cancer detection using deep learning model is presented in this section. The major contribution of convolutional neural network is its accuracy compared to other network architectures. However, various training procedures are introduced to refine the performances which provide numerous CNN architectures. These architectures perform better than conventional CNN due to its deep feature processing abilities. In this research work, a deep CNN architecture, Visual Geometry Group (VGG-19) is used to detect the breast cancer features from medical images. VGGNet models afford better performance than AlexNet by superseding large kernel-sized filters with various small kernel-sized filters. In order to improve the detection performance of the deep learning models, a support vector machine is used instead of fully connected network architecture. The architecture of the proposed network model is depicted in figure 2.

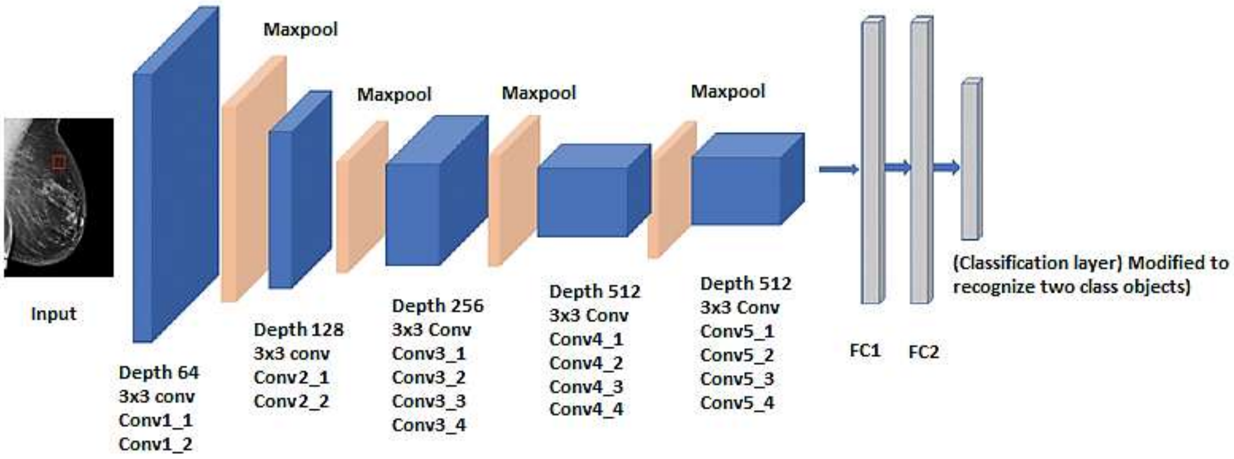

Figure 2: VGG-19Network Architecture

The VGG-19 network architecture consists of l9 layers in which 16 layers are convolution layers and 3 layers are fully connected layers. The accuracy of the deep neural networks increases when the number of layer increases as it can able to process more accurate features. The convolution layers are fully deep trainable and perform convolution operation and it is connected with max-pooling and dropout layers. The convolution layers are simply 3x3 network layers and max-pooling is used to reduce the size of the outputs from the convolution layer. In order to reduce the false positives, the proposed network is trained as an individual lesion and tested with all the lesions. The convolution layer performs convolution operation over every pixel of the input image and passes the output to the next layer. After convolution, an image with n features is generated and these features are obtained based on the convolution layer kernel function. The output of the convolution layer is mathematically formulated as

$$m_i^{(x)} = B_i^{(x)} + \sum_{j=1}^{b_i^{(x-1)}} k_{i,j}^{(x-1)} \times m_j^{(x)} \qquad (1)$$

where$k_{i,j}^{(x-1)}$ represents the convolution kernel or the filter size, $B_i^{(x)}$ represents the matrix bias and the feature maps are obtained as an output function $m_i^{(x)}$. An activation function is applied after the convolution operation so that a nonlinear transfer function is obtained and it is given as

$$n_i^{(x)} = n\left(m_i^{(n)}\right) \qquad (2)$$

Where$n_i^{(x)}$ represents the activation function. various activation functions are available such as Sigmoid Function, Hyperbolic Tangent Function, Rectified Linear Unit (ReLU) Function, etc., In which ReLU is widely preferred due to its computation efficiency. The ReLU function is mathematically expressed as

$$n_i^{(x)} = max\left(0, n_i^{(x)}\right) \qquad (3)$$

The activation function reduces the non-linear effects and interactions by replacing the negative values with zero and processes only the positive values. Next to the convolution layer, max-pooling or sampling layer is used in which the dimensions of the convolution output are reduced. Generally, the sampling process is categorized into maximum pooling, average pooling, and sum pooling and in the proposed work, max pooling is used in which maximum value from each block is considered as the output image pixel. The general architecture of VGG-19 includes three fully connected networks that are used to classify the features obtained from the previous convolution and max-pooling layers. A feed-forward neural network is used to classify the features and the activation function for this layer is the SoftMax activation function which is formulated as

$$n_i^{(x)} = f\left(x_i^{(x)}\right) \qquad (4)$$

where $n_j^{(x)}$ represents the weight functions and f represents the nonlinear transfer function.In the proposed work instead of the feed-forward neural network, a simple and efficient support vector machine is employed to classify the tumor status. The classification performance of support vector machines is better than other classifiers in machine learning algorithms. Since the essential features are selected by the deep network the support vector machine will process the minimum features so that maximum accuracy will be obtained. The supervised learning algorithm finds the optimal hyperplane to separate the feature space. The training datasets are divided into different classes using the high dimensional hyperplane. In case of non-linearly separable data, a kernel support vector machine is used to transfer that data into new vector space. For the given training dataset $D(x_1, y_1), (x_2, y_2), (x_2, y_2), \ldots, (x_n, y_n)$ the decision function for a linear classification is represented as

$$y_i = \left((w \Delta x_i) + b\right) \quad (5)$$

where $x_i \in R^n \rightarrow h$ which is applied to transform the data into high dimensional space. The membership $y_i \in \pm 1$ which represents the label for each action defined in the dataset. The generic hyperplane is obtained based on the following condition

$$w.x_i + b = 0 \quad (6)$$

The hyperplanes are restructured if the margins are delimited and it is given as

$$y_i\left((w.x_i) + b\right) \geq 1 \quad (7)$$

Based on the above functions, the factor which is needed to be minimized to formulate the optimal hyperplane is given as

$$1/2\|w\|^2 \quad (8)$$

The layer details of the proposed architecture are summarized in detail in table 1. The total number of layers, feature maps, size, kernel size, stride, and activation functions are presented.

Table 1. Proposed architecture layer details

Layer	Size	Kernel size	Feature map	Stride	Activation
Conv1_1	224×224×64	3×3	64	1	ReLU
Conv1_2	224×224×64	3×3	64	1	ReLU
Max pooling	112×112×64	3×3	64	2	ReLU
Conv2_1	112×112×128	3×3	128	1	ReLU
Conv2_2	112×112×128	3×3	128	1	ReLU
Max pooling	56×56×128	3×3	128	2	ReLU
Conv3_1	56×56×256	3×3	256	1	ReLU
Conv3_2	56×56×256	3×3	256	1	ReLU
Conv3_3	56×56×256	3×3	256	1	ReLU
Conv3_4	56×56×256	3×3	256	1	ReLU
Max pooling	28×28×256	3×3	256	2	ReLU
Conv4_1	28×28×512	3×3	512	1	ReLU
Conv4_2	28×28×512	3×3	512	1	ReLU
Conv4_3	28×28×512	3×3	512	1	ReLU
Conv4_4	28×28×512	3×3	512	1	ReLU
Max pooling	7×7×512	3×3	512	2	ReLU
Conv3_1	7×7×512	3×3	512	1	ReLU
Conv3_2	7×7×512	3×3	512	1	ReLU
Conv3_3	7×7×512	3×3	512	1	ReLU
Conv3_4	7×7×512	3×3	512	1	ReLU
FCN 1	25088	-	-	-	ReLU
FCN 2	4096	-	-	-	ReLU
FCN	1000	-	-	-	Softmax

The final FCN is a modified network that includes the support vector machine and produces output as two classes as normal and malignant. Based on the features obtained from the previous layers and output is produced. In order to avoid overfitting, the neurons are eliminated randomly in the training stage by the dropout function. The performance evaluation of the proposed breast cancer detection model is presented in the following section.

4. RESULTS AND DISCUSSION

The proposed hybrid deep convolutional neural network performance is evaluated through simulation analysis performed in MATLAB 14.1 installed in an Intel i3 processor with 16GB memory. The operating system is windows 10 anda benchmark dataset such as Wisconsin Breast Cancer Dataset (WBCD) is used and the performances are evaluated in terms of specificity, sensitivity, precision, accuracy, error rate, and processing time. The results obtained from our earlier approaches like Accurate Breast Cancer Detection and Diagnosis Model (ABCDD) which detects cancer using ANN, and Combined Model for Breast Cancer Diagnosis and Staging (CM-BCDS) which detects cancer using Probabilistic Neural Networks (PNN) are considered for analysis along with conventional approach Support Vector Machine (SVM). The simulation settings used for the proposed model experimentation are depicted in the table. 2.

Table 2. Simulation parameters

S. No	Parameter	Range/Value
1	Learning rate	0.0004
2	Batch size	5
3	Maximum epoch	25
4	Optimizer	Adam
5	Classifier	SVM

The dataset considered for analysis is the Wisconsin breast cancer dataset from the UCI machine repository. The diagnostic dataset includes 569 instances with 32 attributes. The total number of classes is 2 which is given as numeric '4' for malignant and '2' for benign. 80% of data is used for training purposes and 10% is used for testing and 10% for validation purposes. A five-fold cross-validation method is followed to validate the performance of the proposed hybrid deep convolutional neural network model.

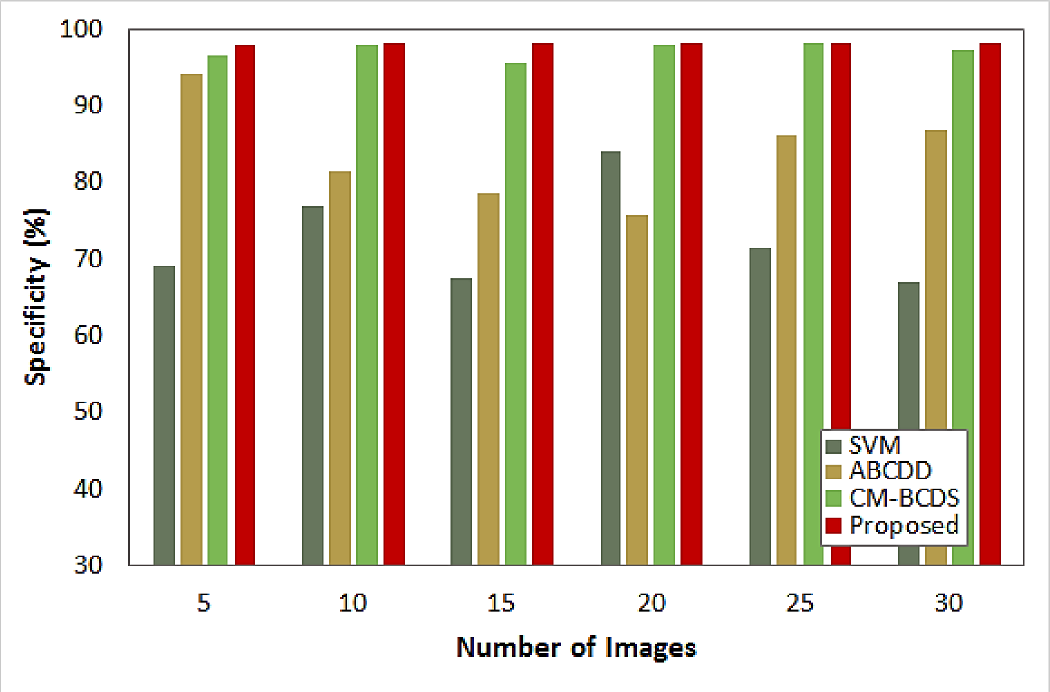

Figure 3: Specificity analysis

Figure 3 depicts the specificity analysis of the proposed model and existing models with different input images. The specificity of the proposed approach is higher than the other models and the average specificity of the proposed model is 98.14% which is more than a percent greater than CM-BCDS, approximately 14% greater than ABCDD, and 25% greater than the conventional support vector machine. The major difference in results between conventional SVM and the proposed hybrid learning model is due to the efficient feature handling capabilities. Conventional SVM processes the data directly using some random feature selection technique but in the proposed approach the optimal features are selected from the dataset so that better specificity is attained by the proposed hybrid deep learning model.

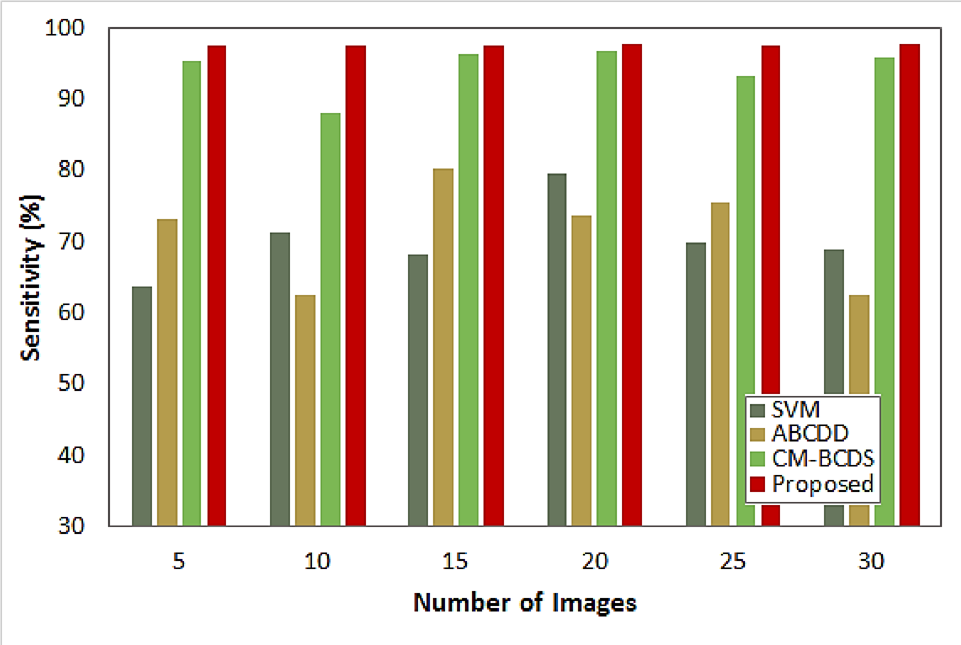

Figure 4: Sensitivity analysis

Sensitivity analysis of the proposed model and existing detection models are compared in figure 4 for different batch sizes. The batch size is increased gradually and the sensitivity performances are observed. It is observed from the results, maximum sensitivity is obtained by the proposed approach even when the batch size is increased to 30. On an average of 98% sensitivity is attained by the proposed approach whereas the sensitivity of CM-BCDS is 94.2%, ABCDD is 71.2% and the support vector machine attains minimum sensitivity of 70.2 % which is 27% lesser than the proposed approach. Similarly, the precision is analyzed in figure 5 for the same batch size and it is observed that maximum precision is attained by the proposed hybrid deep learning approach. the performance of CM-BCDS is slightly near to the proposed performance for smaller batch sizes. However, when the batch size is increased, the precision of CM-BCDS reduces slightly compared to the proposed approach.

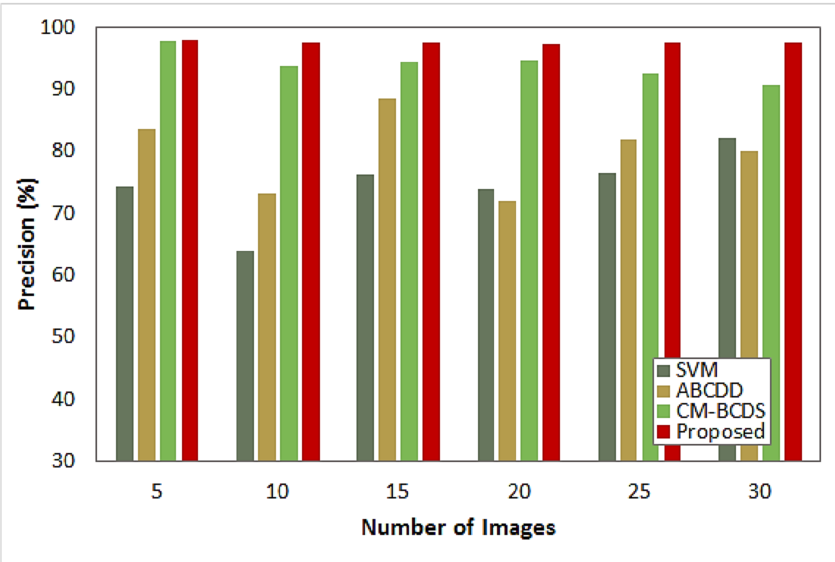

Figure 5: Precision

The error rate for the proposed and existing approaches is analyzed by increasing the batch size to 70. Initially, the error rate is low and it increases gradually when the batch size increases. However, the proposed hybrid deep learning approach attains a minimum error rate compared to other models. Initially, for 20-30 images, the error rate of the proposed approach is 1.2 and it increases gradually and reaches 7.4 for 60-70 images. Whereas the error rate of SVM reaches a maximum of 20.9 for 60-70 images. Followed by SVM the performance of ABCDD is 17.2 for 60-70 images.

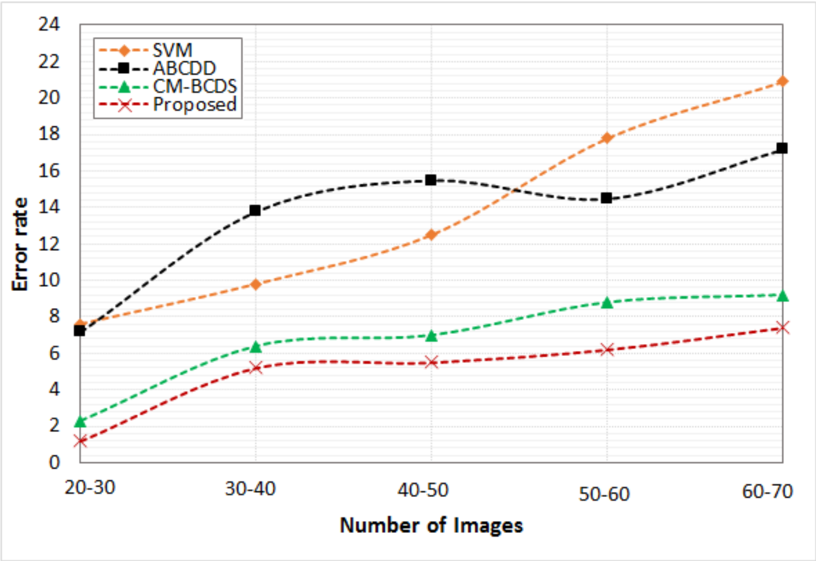

Figure 6: Error rate analyses

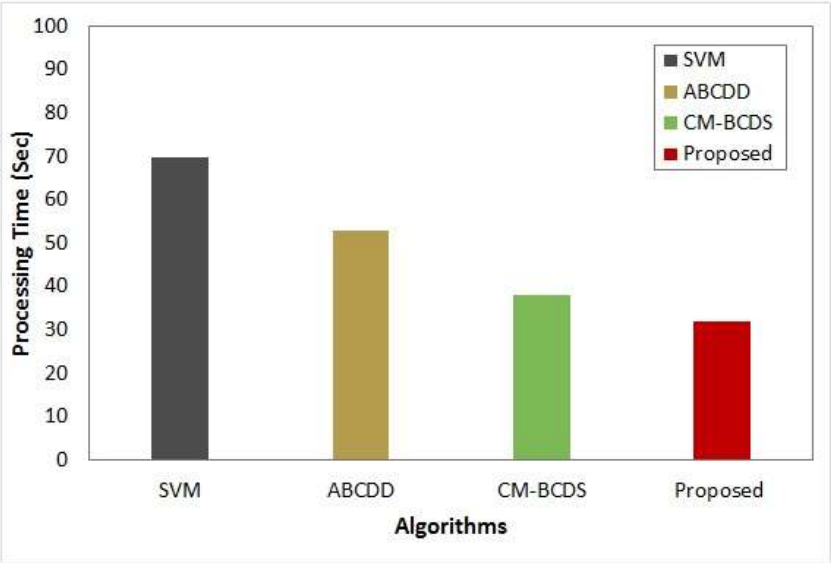

Figure 7: processing time comparison

The processing time is measured for the detection process and compared with existing algorithms. It is observed from the figure, the minimum processing time is attained by the proposed approach whereas maximum processing time is attained by the conventional SVM model. The efficient feature selection and processing through multiple layers reduces the computational complexity of the classifier which further reduces the overall processing time. However, existing approaches like ABCDD and CM-BCDS include multiple techniques for feature selection and extraction which increases the processing time.

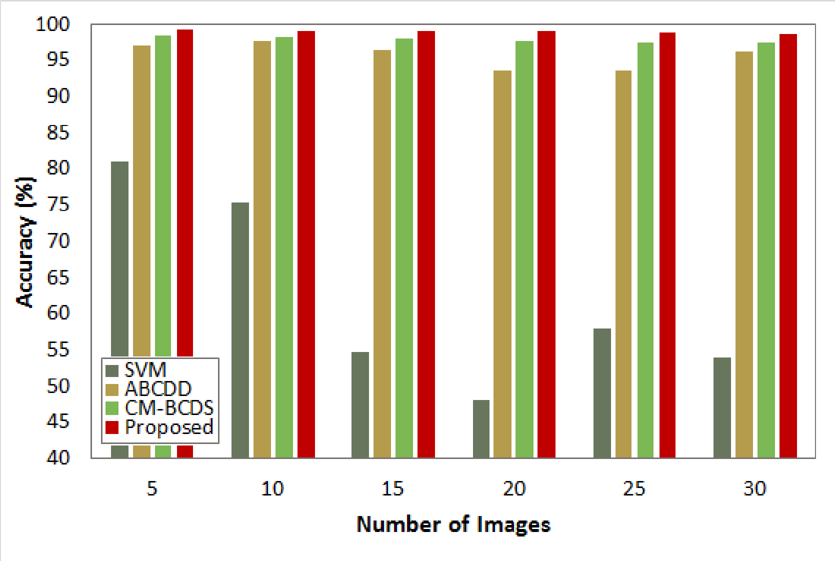

Figure 8: Detection accuracy comparisons

The detection accuracy of the proposed model and existing models are compared and depicted in figure 8. Results clearly demonstrate the superior performance of the proposed approach where 61.8% of accuracy is attained by support vector machine, whereas 95.8% of accuracy is attained by the ABCDD model and 97.8% is attained by the CM-BCDS. The accuracy of the proposed hybrid deep learning model is higher than the other models which indicate superior performance in brain cancer detection.

5. CONCLUSION

In this research work, a hybrid deep learning model is presented to detect breast cancer from mammographic images. VGG-19 deep convolutional neural network is employed in the proposed model and instead of a feed-forward neural network; a support vector machine is used as a classifier. The last fully connected layer is modified and the product is classified through a support vector machine. The essential features which are used to detect the cancer status are obtained using the VGG-19 network. The performances of the proposed model are evaluated and compared with existing detection techniques. The proposed model attains better performances for all the parameters which classify the cancer status with high accuracy. Further, this research work can be extended by concatenating multiple deep learning networks for better performances.

REFERENCES

1. Lauren R. Strang, James Sun, Christine Laronga (2020), "Characteristics of Microinvasive Ductal Carcinoma In Situ Versus Noninvasive and Invasive Breast Cancer" Journal of Surgical Research, vol.254, pp.378-383.
2. Waqar Haque, Ashley Arms, Bin S. The (2019), "Outcomes of pleomorphic lobular carcinoma versus invasive lobular carcinoma" The Breast, vol.43, pp. 67-73.
3. Reid A. Waldman, Justin Finch, Diane Whitaker-Worth (2018), "Skin diseases of the breast and nipple: Benign and malignant tumors" Journal of the American Academy of Dermatology, vol.80, no.6 pp. 1467-1481.
4. Robert H. Hester, Gabriel N. Hortobagyi, Bora Lim (2021), "Inflammatory breast cancer: early recognition and diagnosis is critical" American Journal of Obstetrics and Gynecology, vol.225, no.4, pp. 392-396.
5. Javier Louro, Marta Román, Xavier Castells (2020), "Differences in breast cancer risk after benign breast disease by type of screening diagnosis" The Breast, vol.54, pp.343-348.
6. Elena Provenzano (2019), "Assessment of sentinel lymph nodes for breast cancer" Diagnostic Histopathology, vol.25, no.4, pp.132-137.
7. Jennifer L Caswell-Jin, Sylvia K Plevritis, Lu Tian, Christopher J Cadham, Cong Xu, Natasha K Stout, George W Sledge, Jeanne S Mandelblatt, Allison W Kurian (2018), "Change in Survival in Metastatic Breast Cancer with Treatment Advances: Meta-Analysis and Systematic Review", JNCI Cancer Spectrum, vol.2, no.4, pp. 1-10.
8. Omar Ibrahim Obaid, Mazin Abed Mohammed, Mohd Khanapi Abd Ghani, Salama A. Mostafa, Fahad Taha AL-Dhief (2018), "Evaluating the Performance of Machine Learning Techniques in the Classification of Wisconsin Breast Cancer" International Journal of Engineering & Technology, vol.7, no.4, pp. 160-166.
9. Muhammet Fatih Ak (2020), "A Comparative Analysis of Breast Cancer Detection and Diagnosis Using Data Visualization and Machine Learning Applications" Healthcare, vol.8, no.2, pp. 1-23.
10. Shivangi Singla, Pinaki Ghosh, Uma Kumari (2019), "Breast Cancer Detection using Genetic Algorithm with Correlation based Feature Selection: Experiment on Different Datasets" International Journal of Computer Sciences and Engineering, vol.7, no.4, pp. 1-5.
11. Tsehay Admassu Assegie (2020), "An optimized K-Nearest Neighbor based breast cancer detection" Journal of Robotics and Control, vol.2, no.3, pp. 1-4.
12. Mohammed Abdul Hay Abu Bakr, Haitham Maher Al-Attar, Nader Kamal Mahra, Samy S. Abu-Naser (2020), "Breast Cancer Prediction using JNN" International Journal of Academic Information Systems Research, vol.4, no.10, pp.1-8.

13. Autsuo Higa (2018), “Diagnosis of Breast Cancer using Decision Tree and Artificial Neural Network Algorithms” International Journal of Computer Applications Technology and Research, vol.7, no.1, pp. 23-27.
14. Sahu Bibhuprasad, Mohanty Sachi, Rout Saroj (2019), “A Hybrid Approach for Breast Cancer Classification and Diagnosis” EAI Endorsed Transactions on Scalable Information Systems, vol.6, no.20, pp.1-8.
15. Karthik.S, Srinivasa Perumal.R, Chandra Mouli (2018), “Breast Cancer Classification Using Deep Neural Networks” Knowledge Computing and Its Applications, pp 227-241.
16. Li Shen, Laurie R. Margolies, Joseph H. Rothstein, Eugene Fluder, Russell McBride & Weiva Sieh (2019), “Deep Learning to Improve Breast Cancer Detection on Screening Mammography” Scientific Reports, vol.9, pp.1-12.
17. Manoharan, J. Samuel. (2021) "Study of Variants of Extreme Learning Machine (ELM) Brands and its Performance Measure on Classification Algorithm." Journal of Soft Computing Paradigm (JSCP) 3, no. 02 pp. 83-95.
18. Zohaib Mushtaq, Akbari Yaqub, Shaima Sani & Adnan Khalid (2020), “Effective K-nearest neighbor classifications for Wisconsin breast cancer data sets” Journal of the Chinese Institute of Engineers, vol.43, no.1, pp.80-92.
19. Subham Sadhukhan, Nityasree Upadhyay, Prerana Chakraborty (2019), “Breast Cancer Diagnosis Using Image Processing and Machine Learning” Emerging Technology in Modelling and Graphics. Advances in Intelligent Systems and Computing, vol.937, pp. 113-127.
20. Harikumar Rajaguru, Sannasi Chakravarthy.S.R (2019), “Analysis of Decision Tree and K-Nearest Neighbor Algorithm in the Classification of Breast Cancer” Asian Pacific Journal of Cancer Prevention, vol.20, no.12,pp.3777–3781.
21. Wan Nor Liyana Wan Hassan Ibeni, Mohd Zaki Mohd Salikon, Aida Mustapha, Saiful Adli Daud, Mohd Najib Mohd Salleh (2019), “Comparative analysis on bayesian classification for breast cancer problem”, Bulletin of Electrical Engineering and Informatics, vol. 8, no. 4, pp.1303-1311.
22. Wathiq Laftah Al-Yaseen, Ammar Jehad, Qusay Abdullah Abed, Ali Kadhum Idrees (2020), “The Use of Modified K-Means Algorithm to Enhance the Performance of Support Vector Machine in Classifying Breast Cancer” International Journal of Intelligent Engineering and Systems, vol.14, no.2, pp.1-11.
23. Soundari.D.V, Padmapriya.R, Thirumariselvi.C, Nanthini.N, Priyadharsini.K (2019), “Detection of Breast Cancer Using Machine Learning Support Vector Machine Algorithm” Journal of Computational and Theoretical Nanoscience, vol.16, no.2,pp. 441-444.
24. Ashutosh Kumar Dubey, Umesh Gupta, Sonal Jain (2018), “Comparative Study of K-means and Fuzzy C-means Algorithms on the Breast Cancer Data”, International journal on advanced science engineering information technology, vol.8, no.1, pp. 18-29.
25. Gilal, Abdul Rehman; Abro, Ahsanullah; Hassan, Ghalib; Jaafar, Jafreezal; Rehman, Fazal ur (2019), “A Rough-Fuzzy Model for Early Breast Cancer Detection” Journal of Medical Imaging and Health Informatics, vol.9, no.4,pp. 688-696.
26. Haifeng Wang, Bichen Zheng, Sang Won Yoon, Hoo Sang Ko (2018), “A support vector machine-based ensemble algorithm for breast cancer diagnosis”, European Journal of Operational Research, vol.267, no.2, pp.687-699.
27. Adel S. Assiri, Saima Nazir, Sergio A. Velastin (2020), “Breast Tumor Classification Using an Ensemble Machine Learning Method” Journal of Imagining, vol.6, no.6, pp. 1-13.
28. Huan-Jung Chiu; Tzuu-Hseng S. Li; Ping-Huan Kuo (2020), “Breast Cancer–Detection System Using PCA, Multilayer Perceptron, Transfer Learning, and Support Vector Machine” IEEE Access, vol. 8, pp. 204309-204324.
29. Flavio S. Fogliatto, Michel J. Anzanello, Felipe Soares, Priscila G. Brust-Renck (2019), “Decision Support for Breast Cancer Detection: Classification Improvement Through Feature Selection” Cancer Control, vol.26, pp.1-8.
30. Sutong Wang, Yuyan Wang, Dujuan Wang, Yunqiang Yin, Yanzhang Wang, Yaochu Jin (2020), “An improved random forest-based rule extraction method for breast cancer diagnosis”, Applied Soft Computing,vol.86,pp. 1-34.
31. Qiqige Wuniri; Wei Huangfu; Yaxi Liu; Xiaoli Lin; Liyuan Liu; Zhigang Yu (2019), “A Generic-Driven Wrapper Embedded With Feature-Type-Aware Hybrid Bayesian Classifier for Breast Cancer Classification” IEEE Access, vol. 7, pp. 119931-119942.
32. Abbas S, Jalil Z, Javed AR, Batool I, Khan MZ, Noorwali A, Gadekallu TR, Akbar A.(2021), “BCD-WERT: a novel approach for breast cancer detection using whale optimization based efficient features and extremely randomized tree algorithm”, PeerJ Computer Science, vol.7 pp.
33. Punitha.S, Fadi Al-Turjman, Thompson Stephan (2021), “An automated breast cancer diagnosis using feature selection and parameter optimization in ANN” Computers & Electrical Engineering, vol.90, pp. 1-12.
34. Punitha.S, Amuthan.A, Suresh Joseph.K (2019), “Enhanced Monarchy Butterfly Optimization Technique for effective breast cancer diagnosis” Journal of Medical Systems, vol.43, no.206, pp.1-14.
35. Hu Peng,Wenhua Zhu,Changshou Deng,Kun Yu, Zhijian Wu (2020), “Composite firefly algorithm for breast cancer recognition” Concurrency and Computation Practice and Experience, vol.33, no.5, pp. 1-12.