Electrical and Automation Engineering

Vol: 2(1), 2023

REST Publisher; ISBN: 978-81-956353-5-1

Website: http://restpublisher.com/book-series/eae/

DOI: https://doi.org/10.46632/eae/2/1/9

Detection of Breast Cancer Using Deep Learning Techniques

*** Hirald Dwaraka Praveena, Shaik Saba Samreen, Papaiah Gari Dinesh, Moillakaluva Reddy Lavanya, Mude Sai Yaswanth Naik**

Mohan Babu University Sree Vidyanikethan Engineering College Tirupati, Andhra Pradesh, India.

*Corresponding Author Email: hdpraveena@gmail.com

Abstract. *Evaluation of Histopathology images are a vital approach that is used for the breast cancer detection. To build up the efficiency of breast cancer detection and to reduce the burden of doctors and specialists, we layout various Deep Learning algorithms to recognize most cancers with the usage of histopathology scans. This paper follows several deep learning models like Convolutional Neural network (CNN) and Vgg16 for the recognition method. The dataset we used for class manner is Breast Histopathology Images which contain positive and negative images. We examined breast Histopathology images of 2,77,524 patients of which 198,748 images are IDC (-) and 78,786 images are IDC (+). This shows the deep learning algorithms can greatly facilitate the breast cancer detection, improving the accuracy and speed of detection. One of the most common cancers is Invasive Ductal Carcinoma (IDC). To determine the aggressiveness score to whole-mount specimen, doctors typically focus on areas containing IDC. Therefore, one of the common pre-processing steps for automatic aggressive categorization is to identify the exact region of IDC along the mounting side.*

Keywords*: breast histopathology images, cancer, deep learning, convolutional neural network (CNN), Vgg16.*

1. INTRODUCTION

Breast cancer is the most ordinary cancer, especially among women. Newly diagnosed cancer cases in 2012 accounted for approximately 25% of all cancer cases, or approximately 44,441.67 million cases. Breast cancer is the most ordinary form of cancer in women and is on the rise [1]. Among 4,444 women, the risk of breast cancer is about 4,444: 1 in 8 in the US, 1 in 12 in Europe, and 1 in 40 in Asia (WHO 2008). According to some survey, every 8 minutes women in Indiadie from cervical cancer and there are about 2.5 million cancer cases and more than 7 million new cancer cases in India every year. It is also the most ordinary cancer in women in India, accounting for 27% of all cancers or all cancers. According to earlier research, 1,44,937 cases, 4,444 new cases and 70,218 deaths were recorded in 2012. But in India, the disease beganto increase in the early 1930s and peaked in the 1950s to 1960s. Breast cancer cases were drug resistant, according tothe WHO. Health authorities are investigating one of 4,444 efforts underway to defeat this relentless disease. Screening finds breast cancer earlier makes treatment more efficient. There are many other methods including mammography, ultrasound, CT scanning and MRI. The following sections are organized as follows. Chapter 2 contains a literature review on breast cancer. Chapter 3 presents our approach for processing histopathology images using convolutional neural networks (CNN) and Vgg16, chapter 4 shows the results and chapter 5 includes the discussion.

2. LITERATURE REVIEW

Hirra et al **[1]** come up with an algorithm. According to this survey, the come-up model is Pa-DBN-BC for the identification of cancer using histopathological scans. The proposed method automatically extracts features by creating equal sized patches from images. The results conclude that the deep learning model improves the efficiency and accuracy of cancer case classification.

K. Das et al **[2]**conducted a detailed study of different methods where Whole- slide histopathological imaging (WSI) has become the standardfor cancer detection. Computer vision reduces the work load ofdoctors and for this detection convolution neural network (CNN) is best choice. The Performance of methods was estimated using the breast cancer dataset like Break His, IUPHL and UCSB. where, 83% of accuracy is accomplished.

G. Wadhwa et al **[3]** come up with a new deep learning algorithmlike CNN to improve categorization results on the dataset like Break His. The purpose of this algorithm is to help physicians detect and diagnose cancer. In this model features are extractedwith the help of above-mentioned algorithm. The results have shown the greater accuracy of 95.58%.

Z. Wang et al **[4]** come up with a computer-aided diagnostic system dependent on mammography enable the advance detection, identification and therapy of breast cancer. First,they proposed a quality detection algorithm based on CNN andExtreme Learning Machine (ELM) clustering. ssecondly, they construct a characterization set for merging all features. Thirdly Extreme Learning Machine (ELM) was proposed for categorization of cancer.

3. METHODOLOGY

Figure-1 shows a framework to illustrating the cancer detectionfrom breast histopathology images.

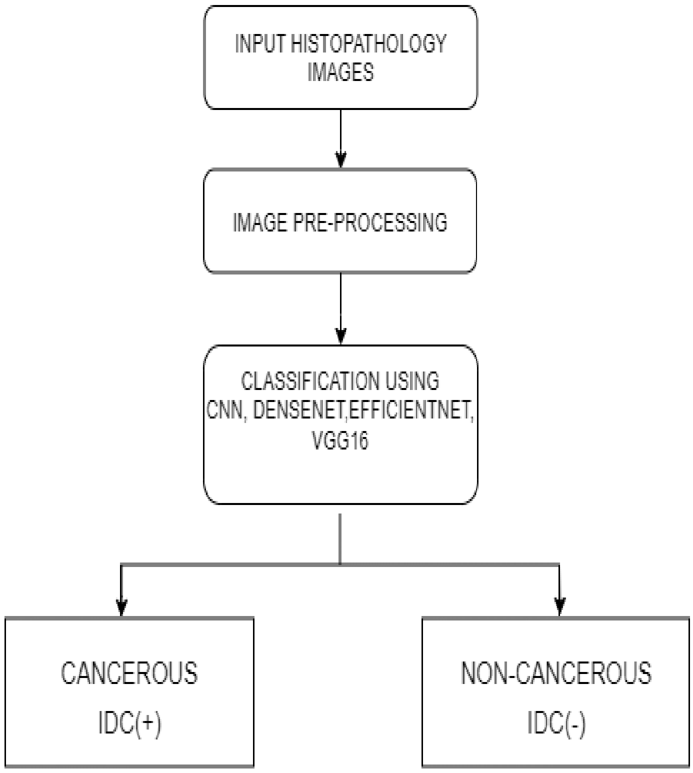

FIGURE 1. Framework for identification of cancer

Firstly, the process starts to obtain breast histopathology images of cancer patients. For research purposes these histopathology scans have been taken from open-source datasetavailable on Kaggle. The database contains images of cancer and non-cancer cases. Then the Image pre-processing step aims to reduce any unwanted distortion already present in the image. This image pre-processing includes two main steps of image enhancement and image smoothing. To remove unwanted noise from the image, we apply smoothing. To achieve better results from further processing, image enhancement techniques are used to improve the quality of digital histopathology images. The final step is the detection step, where efficient algorithms such as CNN and VGG16 are used to classify the breast histopathology images into IDC (+) which means cancer is present and IDC (-) where cancer is absent. The results obtained are compared to select the best breast cancer detection algorithm. *Dataset*-The dataset used for the proposed system is Breast histopathology images which are available in Kaggle. Thisdata set contains benign and malignant images. The dataset includes 2,77,524 MR images, of which 198,748 are labeled asIDC (-). The other 78,786 scans are marked as IDC (+). The final output of the model comes from the accurate processing of the test results.

Convolutional Neural Networks

Convolutional neural networks (CNN) are designedspecifically for image processing (IP) and it is thoroughly used in computer vision. These have become a research hotspot in computer vision areas such as image recognition, detection andsegmentation [2-3]. It is a well-established technique in the department of medical imaging. The breast MR image layers of the CNN Architecture are shown in Figure-2.

Among various deep learning methods, CNN is considered as the dominant deep learning method. CNNs are the most widely used configuration in MRI and other image processing applications. It also has great advantages in image categorization and has gained good results in many object recognition problems, especially since the network itself can extract multi-level features from images [5]. This DL process that takes various elements of an image and prioritizes them so that they can be distinguished from each other. In this network,each convolutional layer is used to extract a different set of features from a set of images

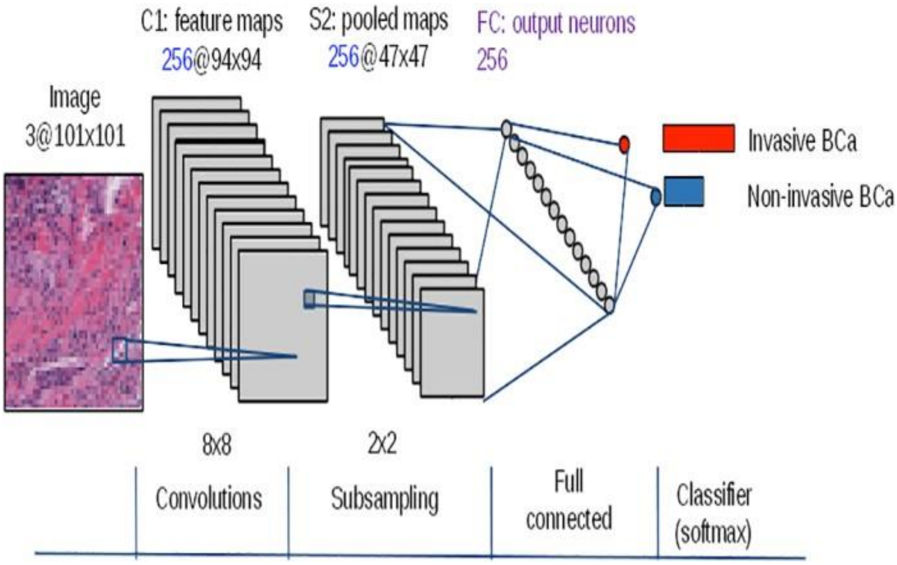

FIGURE 2. Layers in CNN Architecture

VGG16:

VGG16 is a deep convolutional neural network method which was introduced by Simonyan and Zisserman. It is still considered one of the best and most efficient models available today. A deeper VGG model can help the kernel learn more complex features. In a survey, it was developed that the pre- trained and fine-tuned which refers to utilizing transfer learning VGG16 achieved elevated accuracy than the fullytrained network [10]. The architecture of the VGG16 model does not have a large number of parameters, but instead focuses on ConvNet layers with a 3x3 core size. It stands out for its simplicity compared to other complete products that have been developed. The minimum expected input image size for the model is 224x224 pixels with three channels. Figure-3 shows a standard VGG 16 network architecture.

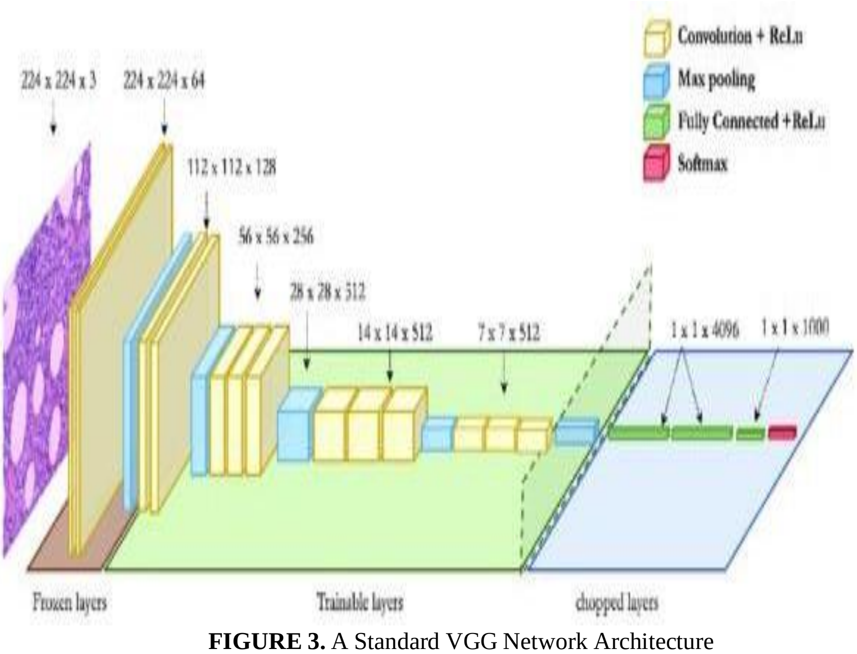

FIGURE 3. A Standard VGG Network Architecture

In the above representation of modified and fine-tuned VGG16architecture, the first block is frozen, while the remaining layers can be trained.

4. RESULTS

To detect the breast cancer, the optimal use of CNN, Dense Net, Efficient Net and VGG16 is studied.

CNN

Figure-4 shows the breast histopathology image having cancer and Figure-5 shows the image with no cancer respectivelyusing CNN. Figure-6 shows the graphical representation of the model accuracy and model loss depicted during detection of breast cancer.

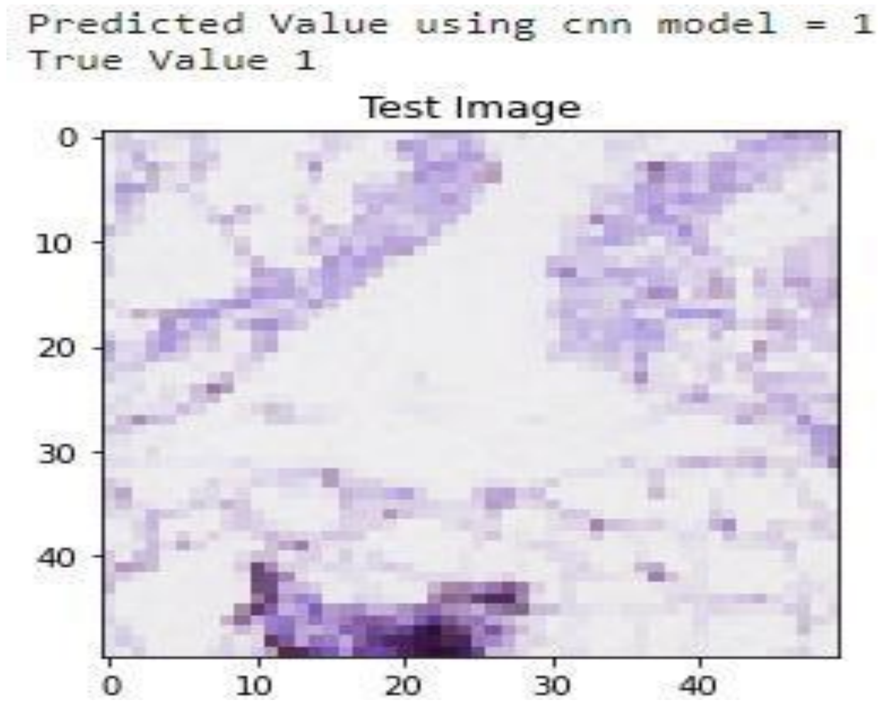

FIGURE 4. Cancerous

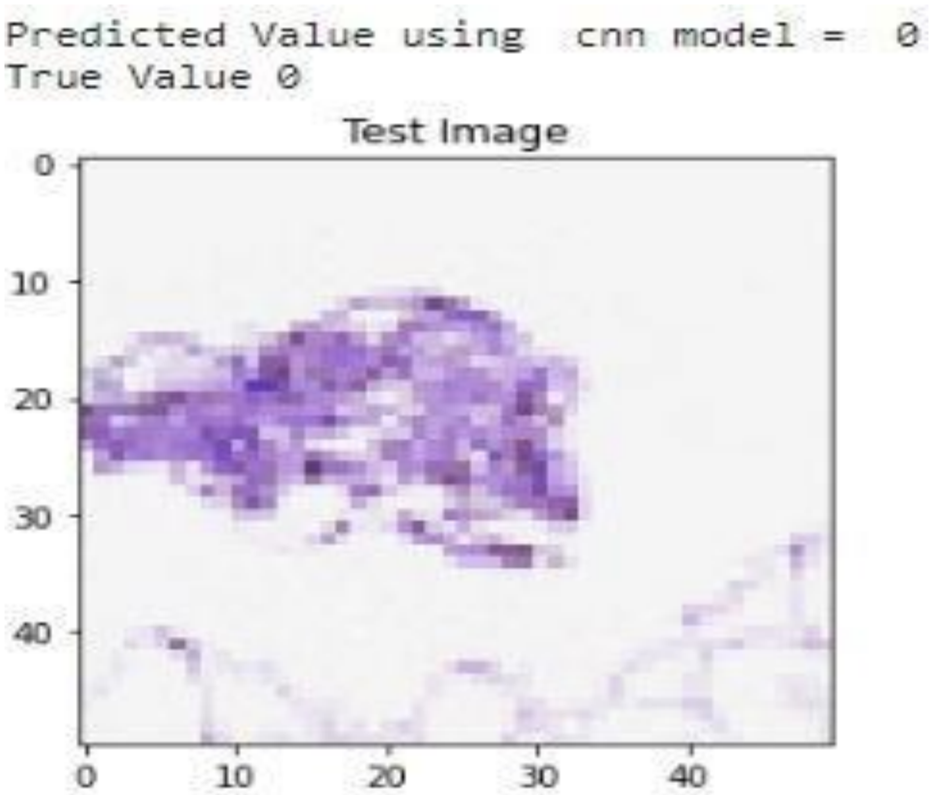

FIGURE 5. Non-Cancerous

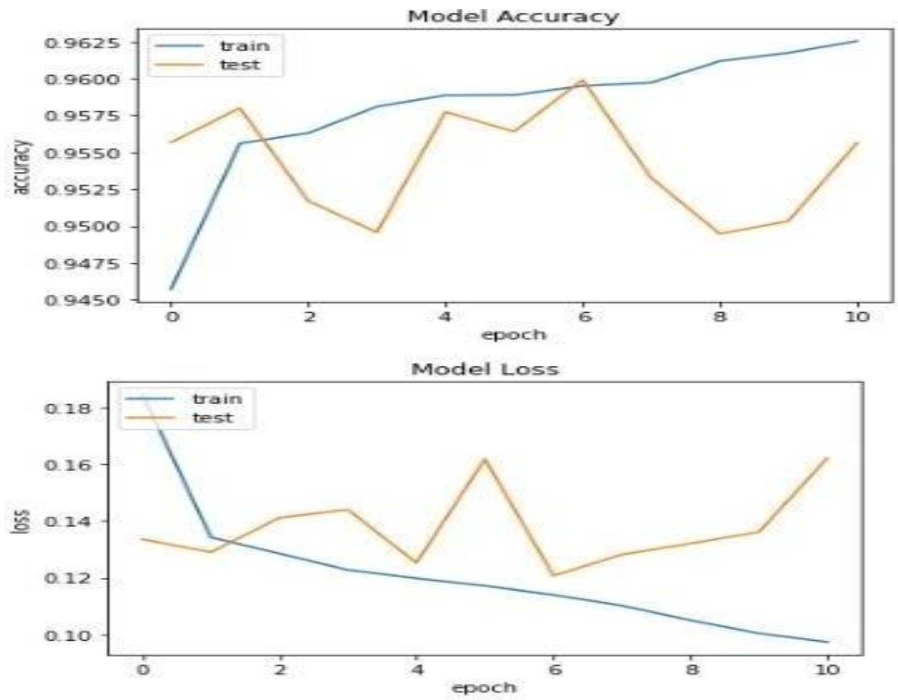

FIGURE 6. Graphical Representation of model accuracyand model loss for CNN

VGG 16

Figure-7 shows the breast histopathology image having cancer and Figure-8 shows the image with no cancer respectivelyusing VGG16. Figure-9 shows the graphical representation of the model accuracy and model loss depicted during detection

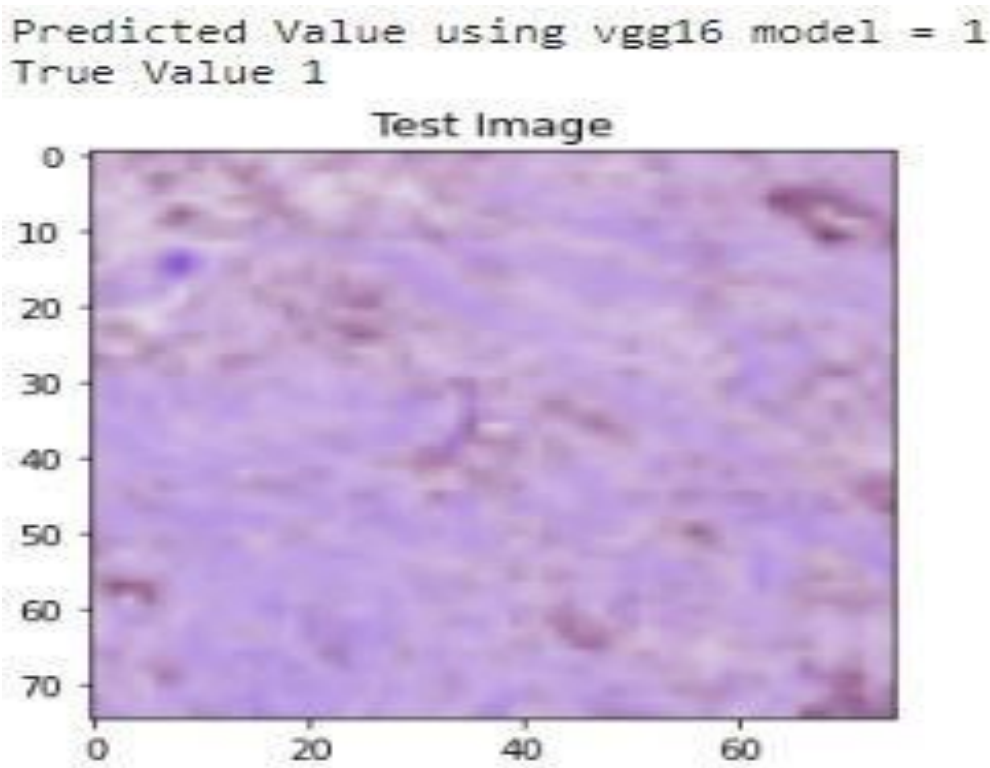

FIGURE 7. Cancerous

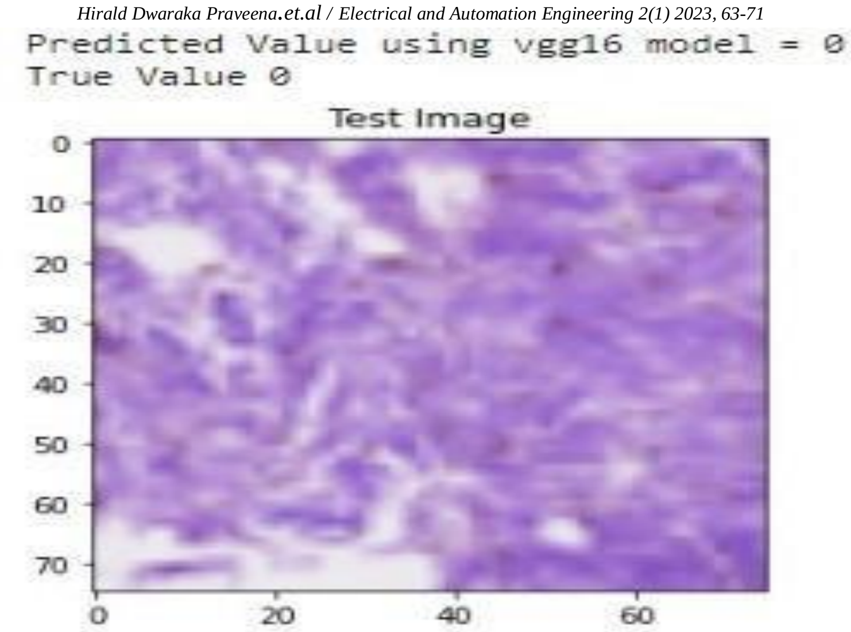

FIGURE 8. Non-Cancerous

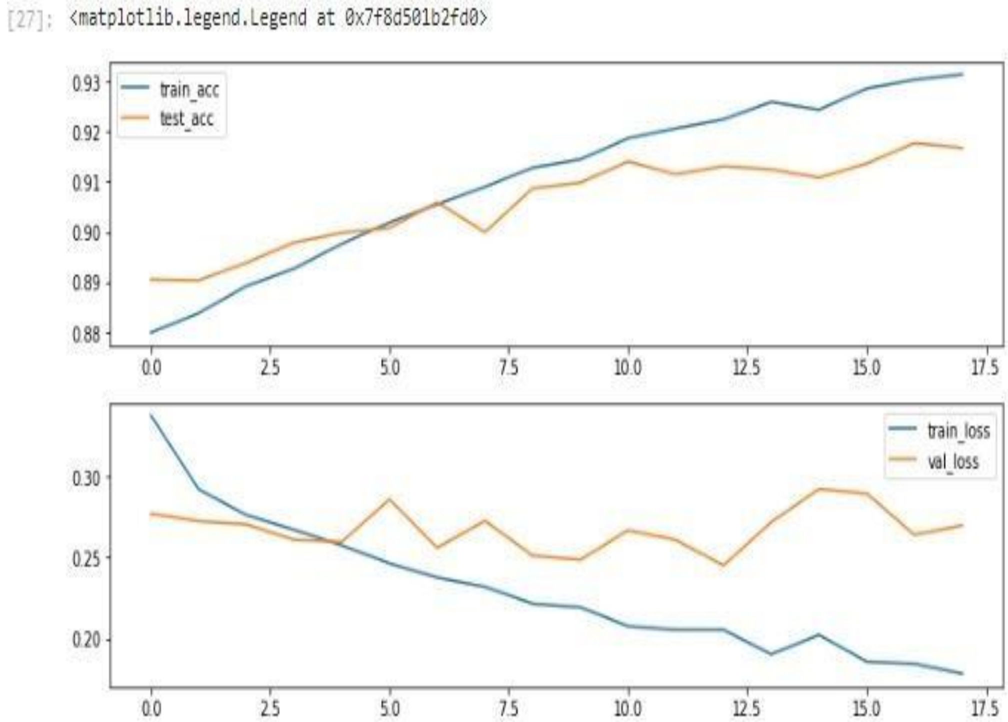

FIGURE 9. Graphical Representation of model accuracyand model loss for VGG16

The performance metrics of the below comparison Table1 is obtained from the confusion matrix such as recall, precision and accuracy with the help of below formulas:

1. Recall = tp/(tp+fn)
2. Precision = tp/(tp+fp)
3. F1score=2*{(Precision*Recall)/ (precision+ Recall)}
4. Accuracy=tp+tn/(tp+tn+fp+fn)

Where, tp=true positive
tn=true negative
fp=false positive
fn=false negative

TABLE 1. Comparison of performance metrics of existing andproposed methods for CNN and VGG16 Classifiers

Classifier	Recall(%)	Precision(%)	F1-Score(%)	Accuracy(%)
CNN [3]	99	90	89	95.58
VGG16[5]	80	95.07	90.84	86.42
CNN	97.01	98.38	97.69	96.25
VGG16	94.71	95.49	95.09	92.29

The graphical representation in figures-10, 11, 12, 13 showsthe performance measures like recall, precision, F1-Score and accuracy for existing and proposed models with CNN andVGG16 classifiers.

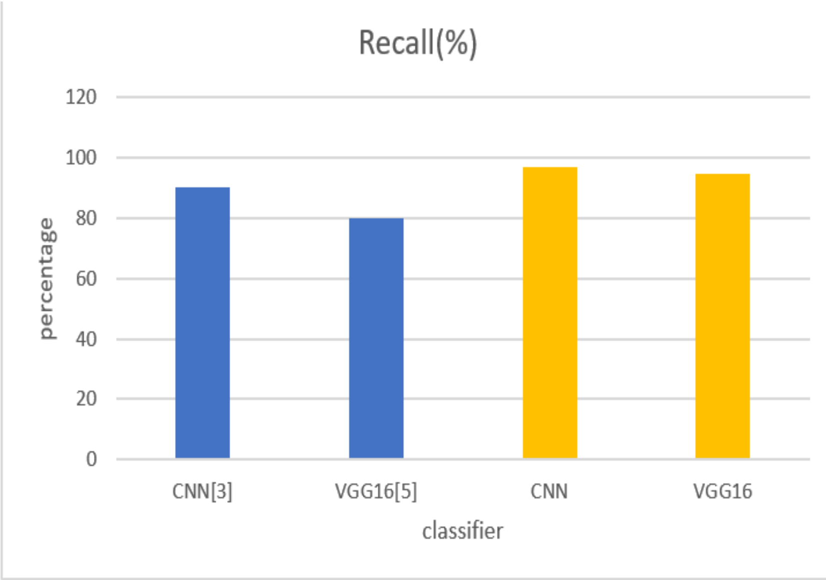

FIGURE 10. Graphical Representation of Recall for existing andproposed methods with CNN and VGG16 models.

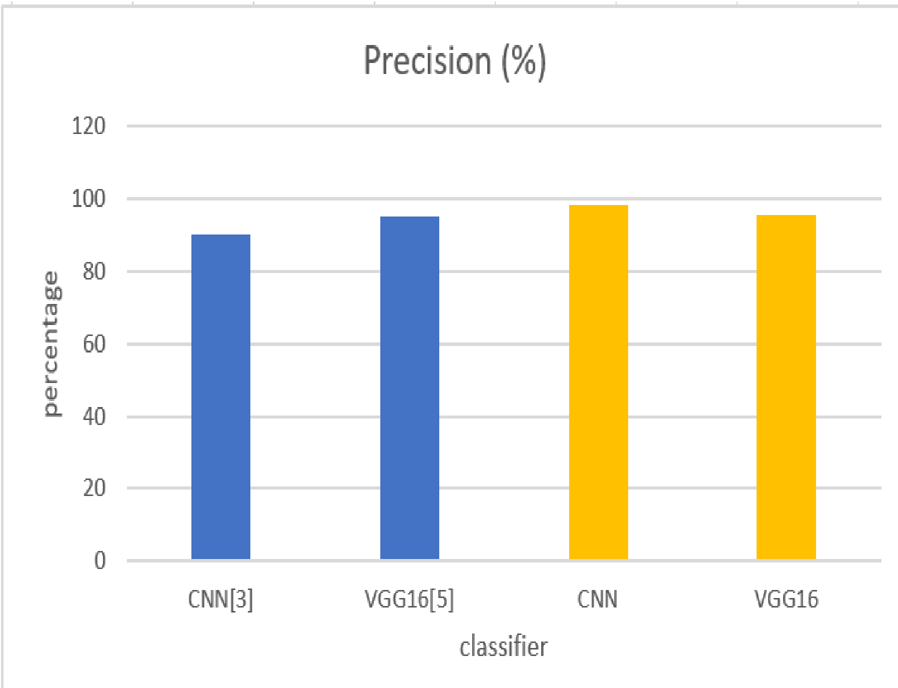

FIGURE 11. Graphical Representation of Precision for existingand proposed methods with CNN and VGG16 models.

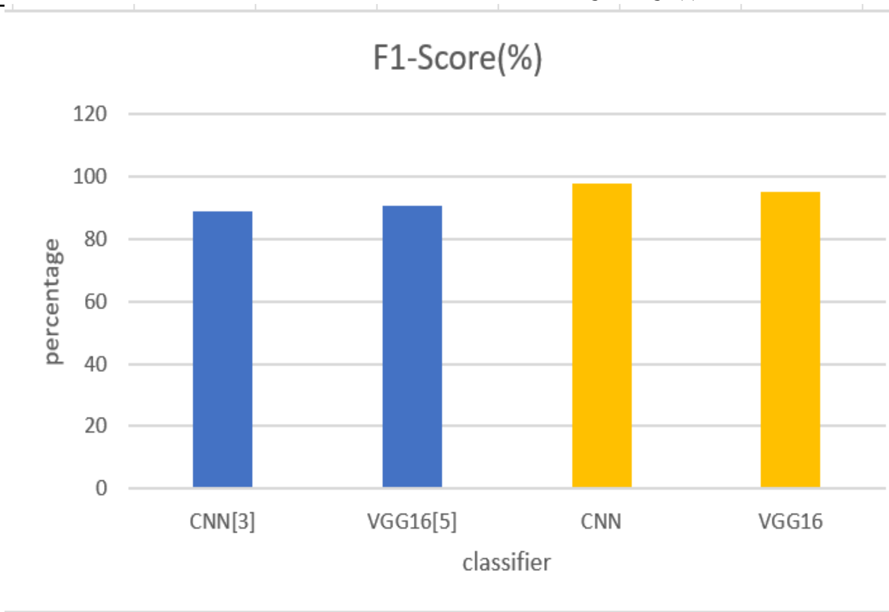

FIGURE 12. Graphical Representation of F1-Score for existingand proposed methods with CNN and VGG16 models.

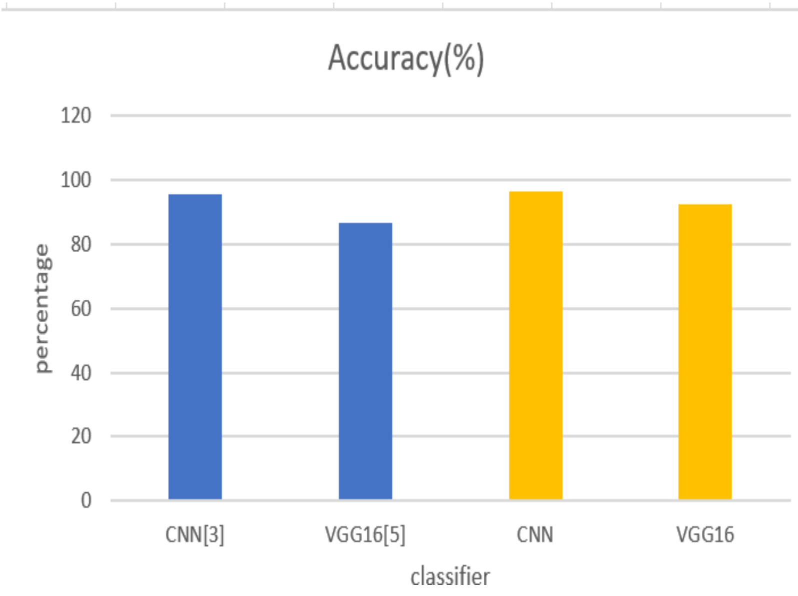

FIGURE 13. Graphical Representation of Accuracy's for existing and proposed methods with CNN and VGG16 models

5. CONCLUSION

The study range over the implementation of deep learning models in breast cancer detection. Extracting high-levelfeatures from histopathological images helps improve the efficiency of the diagnostic process. In this survey, various deep learning methods such as CNN and VGG16 are examine and the corresponding results are compared toselect the best performing CNN algorithm to detect thebreast cancers from Breast Histopathology images. Extensive experiments were conducted on the Breast Histopathology Images and a set of performance measures were to evaluate performance. The top performing model, CNN showed the highest accuracy of 96.25% among all themodels presented in this survey.

REFERENCES

[1]. Sharawi, M. S., Aloi, D. N., & Rawashdeh, O. A. "Design and implementation of embedded printed antenna arrays in small UAV wing structures" IEEE Transactions on Antennas and Propagation 2010, 58(8), 2531- 2538.
[2]. Nosrati, M., Jafargholi, A., Pazoki, R., & Tavassolian, N. "Broadband slotted blade dipole antenna for airborne UAV applications" IEEE Transactions on Antennas and Propagation 2018, 66(8), 3857-3864.
[3]. Kapoor, A., Kumar, P., & Mishra, R. "High gain modified Vivaldi vehicular antenna for IoV communications in 5G network"

Heliyon 2021, 8(5), e09336.
[4]. Kumar, P., & Masa-Campos, J. L. "Dual polarized monopole patch antennas for UWB applications with elimination of WLAN signals" Advanced Electromagnetics 2016, 5(1), 46-52.
[5]. Zong, Y., Ding, J., Guo, C., & Zhang, J. "An improved broadband multi-layer dual-polarized antenna for UAV radars" International Conference on Microwave and Millimeter Wave Technology (ICMMT)2010, (pp. 1-3).
[6]. Sarath, J. V., BIJU, K., & RANI, L. "REVIEW OF ANTENNAS USED IN FPV/WLAN APPLICATIONS" Acta Technica Corviniensis-Bulletin of Engineering 2021, 14(1).
[7]. Sano, M., & Higaki, M. "A linearly polarized patch antenna with a continuously reconfigurable polarization plane" IEEE Transactions on Antennas and Propagation 2019, pp. 5678-5683.
[8]. Imran, A. Z. M., Hakim, M. L., Ahmed, M., Islam, M. T., & Hossain, E. "Design of microstrip patch antenna to deploy unmanned aerial vehicle as UE in 5G wireless network. International Journal of Electrical & Computer Engineering 2021, 2088-8708), 11(5).
[9]. Mozaffari, M., Saad, W., Bennis, M., Nam, Y. H., & Debbah, M. "A tutorial on UAVs for wireless networks: Applications, challenges, and open problems" IEEE communications surveys & tutorials 2019, pp 2334-2360.
[10]. Chamola, V., Kotesh, P., Agarwal, A., Gupta, N., & Guizani, M. (2021). A comprehensive review of unmanned aerial vehicle attacks and neutralization techniques. Ad hoc networks, 111, 102324.
[11]. Imran, A. Z. M., Hakim, M. L., Ahmed, M., Islam, M. T., & Hossain, E. "Design of microstrip patch antenna to deploy unmanned aerial vehicle as UE in 5G wireless network" International Journal of Electrical & Computer Engineering,2021, (2088-8708), 11(5).
[12]. Yusuf, A. M., & Wijanto, H. "Dual CX-Band E-Shaped Microstrip Antenna Array 1× 8 for Synthetic Aperture Radar on UAV" IEEE International Conference on Signals and Systems 2019, pp. 186-189.
[13]. Valavanis, K. P., & Vachtsevanos, G. J. (Eds.) "Handbook of unmanned aerial vehicles" (Vol. 1), Dordrecht: Springer 2015 Netherlands.
[14]. Arpaio, M. J., Fuschini, F., Vitucci, E. M., Degli Esposti, V., Barbiroli, M., & Masotti, D "Lightweight Microstrip Patch Array for Broadband UAV Applications over 5G networks" Conference on Microwave Techniques 2019, pp. 1-5.
[15]. Imran, A. Z. M., Hakim, M. L., Ahmed, M., Islam, M. T., & Hossain, E. "Design of microstrip patch antenna to deploy unmanned aerial vehicle as UE in 5G wireless network" International Journal of Electrical & Computer Engineering 2021,2088-8708, 11(5).
[16]. Seo, D. G., Ahn, S. H., Jeong, C. H., & Lee, W. S. "UAV Communication Antenna Array with Wide Coverage Multi-beam 3× 2 Switched Beamforming Network" IEEE Radio and Wireless Symposium (RWS) 2019, pp. 1-4.
[17]. Kang, D., Tak, J., & Choi, J. "Wideband low-profile planar square segmented loop antenna for UAV applications" Electronics Letters 2016, 52(22), 1828-1830.
[18]. T. Naresh Babu, M. Ramachandran, Sathiyaraj Chinnasamy, Ashwini Murugan, "The Evaluation of Third-party Logistics Services Using Complex Proportional Assessment", REST Journal on Banking, Accounting and Business, 1(4), (2022): 14-22
[19]. Yang, X., Qi, Y., Yuan, B., Cao, Y., & Wang, G. "A miniaturized high-gain flexible antenna for UAV applications" International Journal of Antennas and Propagation 2021, pp 1-7.
[20]. Jain, K., & Kushwah, V. S. "Compact, broadband, and thin corrugated U-shaped patch-constituted MIMO antennas for airborne UAV applications" International Journal of Microwave and Wireless Technologies 2022, pp. 1-10.
[21]. Mustaqim, M., Khawaja, B. A., Razzaqi, A. A., Zaidi, S. S. H., Jawed, S. A., & Qazi, S. H. "Wideband and high gain antenna arrays for UAV-to-UAV and UAV-to-ground communication in flying ad-hoc networks (FANETs)" Microwave and Optical Technology Letters 2018, 60(5), pp 1164-1170.
[22]. Nosrati, M., Jafargholi, A., & Tavassolian, N. "A broadband blade dipole antenna for UAV applications" IEEE International Symposium on Antennas and Propagation (APSURSI) 2016, pp. 1777-1778
[23]. Yoon, S., Tak, J., Choi, J., & Park, Y. M. "Conformal monopolar antenna for UAV applications" IEEE International Symposium on Antennas and Propagation & USNC/URSI National Radio Science Meeting 2016, (pp. 517-518.

