Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 16, Issue. 1: 2025
ISSN : **1906-9685**

Deep Learning for Breast Cancer Disease Detection

Ms. Guna Gayathri Praseetha K[1], Chundi Snehalatha Reddy[2], Chilakapati Maneesha[3], Y Giri[4], Kuthala Venkatesh[5]

#1Assistant Professor in Department of CSE, PBR Visvodaya Institute of Technology & Science,KAVALI
#2#3#4#5 B.Tech with Computer Science & Engineering,VISVODAYA ENGINEERING COLLEGE,KAVALI

Abstract: The most common cause of cancer-related deaths among women is breast cancer. The best and most efficient way to slow the growth of tumours is to discover and diagnose them early. The imaging technique now advised for the early detection and diagnosis of breast cancer is mammography. Classifying masses in mammograms remains a significant difficulty and is essential to helping radiologists make an accurate diagnosis. One deep learning methodology that we provide in this study is a classification method based on convolution neural networks (CNNs).

Index terms - *breast cancer detection, deep learning, convolutional neural networks, mammography, MobileNet, Inception V3, image classification, computer-aided diagnosis, medical imaging, tumor detection, feature extraction, X-ray imaging, breast mass classification, early cancer diagnosis*

1. INTRODUCTION

One of the most prevalent types of cancer among women nowadays is breast cancer. About 246,660 women received a breast cancer diagnosis in 2016, which is thought to be the highest percentage of any cancer kind at 29%. Breast cancer is second in women's predicted deaths, accounting for 14% of all cancer-related fatalities. In the United States, almost 40,000 people lose their lives to breast cancer every year. To improve the survival rate, early detection and accurate diagnosis are crucial. Mammography is a commonly used diagnostic technique in clinical practice to test for breast cancer [1]. Low doses of X-ray radiation are applied to the patient's breasts during a mammogram. Because normal and malignant tissues absorb X-rays at different rates, breast cancer can be identified using mammography. On mammograms, tumours may show up as masses, asymmetry, distortions, hypothesised masses, or microcalcifications [2]. Due to the volume of breast pictures they must review every day and the difficulty of reading the images (i.e., identifying the breast masses and properly diagnosing them), radiologists have difficulties in accurately detecting and diagnosing breast cancer (i.e., normal and abnormal) [3]. Therefore, computer-aided detection and diagnosis (CAD) is crucial for giving doctors a second view to help and support their choices [4]. Using several nonlinear processing layers, the rapidly emerging discipline of deep learning investigates aspects of machine learning and artificial intelligence to extract characteristics straight from the data [5]. One of the most potent machine-learning tools for image classification is deep learning with convolutional neural networks, which outperforms practically all other conventional classification techniques and even human ability in terms of accuracy [6, 7]. By lowering the size of input data while keeping the most significant differential characteristics, the convolutional technique may reduce a picture with millions of pixels to a collection of tiny feature maps [8]. To identify the whole mammograms, we are using two CNN architectures: Mobile-Net and Inception V3. Google researchers created the CNN class known as MobileNet. The foundation of Mobie-Nets is a simplified architecture that creates lightweight deep neural networks using depth-wise separable convolution. The primary distinction between the Mobile-Net design and conventional CNNs is that Mobile-Net divides the convolution into a 3X3 depth-wise convolution and a 1X1 point-wise convolution, rather than using a single 3X3 convolution layer followed by batch norm and ReLU. Szegedy et al. originally presented the Inception architecture in 2014. The inception module's objective is to compute 1x1, 3x3, and 5x5 convolutions inside the same network module in order to function as a "multilevel feature extractor." Prior to being sent into the network's subsequent layer, the output of these filters is stacked along the channel dimension.

2. LITERATURE SURVEY

2.1 Prediction of pathological complete response after neoadjuvant chemotherapy in breast cancer by combining magnetic resonance imaging and core needle biopsy

https://www.sciencedirect.com/science/article/abs/pii/S0960740420304102

ABSTRACT:

Context

Neoadjuvant chemotherapy (NAC) frequently results in pathological complete response (pCR), especially in hormone receptor-negative breast cancer. The most dependable imaging technique for assessing the pathogenic impact of NAC is contrast-enhanced magnetic resonance imaging (cMRI). When using core needle biopsy (CNB) to get representative specimens from the target lesion, ultrasound is essential. In instances with full clinical response (cCR) identified by cMRI, the purpose of this study was to assess the predictive accuracy of pCR by adding CNB following NAC.

Techniques

We assessed individuals with cCR by cMRI following NAC in this prospective multicenter investigation. As intended, ultrasound-guided CNB (uCNB) was carried out under general anaesthesia with a 14G needle and no clip markers. The uCNB-collected specimens were classified as (i) no cancer (ypT0), (ii) no invasive carcinoma and just residual carcinoma in situ (ypTis), and (iii) residual invasive carcinoma after being compared to surgically removed specimens. It was assessed if the pathological findings from the surgical specimens and the uCNB were consistent.

Findings

41 (49.4%) and 17 (20.5%) of the 83 individuals that were assessed had ypT0 and ypTis, respectively. For

predicting ypT0 by uCNB, the corresponding false negative rates (FNR), sensitivity, and specificity were 50.0%, 50.0%, and 100%; for predicting ypT0+ypTis, they were 28.0%, 72.0%, and 98.3%, respectively. For ypT0, the concordance rates were 74.7% (62/83) and for ypT0+ypTis, they were 90.4% (75/83).

In conclusion

uCNB was insufficiently accurate to predict pCR in cCR patients identified by cMRI. For improved prediction, other modalities, such as clip locations and/or larger core needles, would be needed.

2.2 Results of a nationwide survey on Japanese clinical practice in breast-conserving radiotherapy for breast cancer

https://pmc.ncbi.nlm.nih.gov/articles/PMC6373682/

ABSTRACT: A statewide questionnaire study on the clinical use of postoperative radiation for breast-conserving treatment of breast cancer was carried out by the Japanese Radiation Oncology Study Group's Breast Cancer Group. These 18 questions covered topics such as the number of patients treated each year, planning method, contouring structure, field design, dose-fractionated regimen, hypofractionated radiotherapy application, boost irradiation, radiotherapy for synchronously bilateral breast cancer, and accelerated partial breast irradiation. A total of 293 Japanese hospitals responded to the online survey. The findings showed the following: Treatment planning is carried out using comparatively similar field designs and delivery methods; over one-third of institutes use the field-in-field technique; the most common criteria for boost irradiation are based on the surgical margin width (5 mm) and age (40 or 50 years), though some facilities used a different age criterion (>70 years) to omit a tumour bed boost; for conventional fractionation, nearly all institutes delivered 10 Gy in five fractions to the tumour bed and 50 Gy in 25 fra According to this survey, hypofractionated radiotherapy was available in 43% of institutions, with the most popular regimens being 10.64 Gy in 4 fractions for boost irradiation and 42.56 Gy in 16 fractions for whole-breast irradiation. Accelerated partial breast irradiation was not commonly available in Japan, and nearly all of the facilities treated both breasts at the same time for synchronised bilateral breast cancer. An overview of radiotherapy's current clinical use in Japan for breast-conserving breast cancer treatment was given by this survey.

2.3 Breast cancer screening (BCS) chart: a basic and preliminary model for making screening mammography more productive and efficient

https://pubmed.ncbi.nlm.nih.gov/28505346/

ABSTRACT: Background: To increase the effectiveness of screening mammography, the breast cancer screening (BCS) chart is recommended as a fundamental and initial tool.

Methods: In this case-control research, which was carried out in 2016, we recruited 1422 women between the ages of 30 and 75, 506 of whom had breast cancer (cases) and 916 of whom did not (controls). We used a multivariate logistic regression analysis to create the BCS graphic. To estimate each person's personal risk of breast cancer, we aggregated the hazards of the disease. The estimated risk probabilities were then classified and coloured as follows: <05% (green), 05-09% (yellow), 10-14% (orange), 15-19% (red), 20-24% (brown), and ≥25% (black).

Results: Based on factors including age, body mass index, late menopause, having a benign breast illness, and a positive family history of breast cancer among first-, second-, or third-degree relatives, the BCS chart shows the risk likelihood of breast cancer. A person can be categorised as having a low risk of breast cancer (green), a medium risk (yellow and orange), a high risk (red and brown), or a very high risk (black) based on this chart.

Conclusions: This chart is a versatile and user-friendly tool that may identify high-risk individuals and improve the effectiveness and efficiency of the screening program.

2.4 Representation learning for mammography mass lesion classification with convolutional neural networks

https://pubmed.ncbi.nlm.nih.gov/26826901/

ABSTRACT: Context and goal: Currently, there is no solution for automatically classifying lesions from breast imaging. In order to circumvent the need to create specialised hand-crafted image-based feature detectors, this research presents a novel representation learning framework for mammography-based breast cancer detection that incorporates deep learning techniques to automatically learn discriminative features.

Methods: A new biopsy-proven benchmarking dataset was constructed from the cases of 344 patients with breast cancer. It included 736 film mammography (mediolateral oblique and craniocaudal) views, as well as 426 benign and 310 malignant lesions that were manually segmented as mass-related lesions. The two primary steps of the developed technique are (i) preprocessing to improve image details and (ii) supervised training to build the classifier for breast imaging lesions as well as the characteristics. Unlike other studies, we take a hybrid method in which the representation is learnt in a supervised manner using convolutional neural networks rather than by creating specific descriptors to describe the content of mammography pictures.

Results: Our method outperforms state-of-the-art image descriptors like histogram of orientated gradients (HOG) and histogram of the gradient divergence (HGD), as shown by experimental results using the developed benchmarking breast cancer dataset. The performance increased from 0.787 to 0.822 in terms of the area under the ROC curve (AUC). It's interesting to note that this model actually performs better than a collection of manually created features that utilise extra data from the radiologist's segmentation. Ultimately, the optimal descriptor for mass lesion categorisation was produced by combining the two representations—learned and hand-crafted—achieving an AUC score of 0.826.

Conclusions: A new deep learning framework was created to automatically classify breast mass lesions in mammograms.

2.5 DeepSplice: Deep classification of novel splice junctions revealed by RNA-seq

https://ieeexplore.ieee.org/document/7822541

ABSTRACT: A single multi-exon gene can produce several mRNA transcripts through a controlled process called alternative splicing (AS). Splice junctions and splice sites may now be predicted using spliced alignment to the reference genome thanks to the availability of large-scale RNA-seq datasets. This significantly improves the capacity to analyse the variety of splicing variants and interpret gene architecture. However, because of sequence mistakes and random sequence matches, current ab initio aligners are susceptible to false positive spliced alignments. In downstream investigations of splice variant discovery and abundance estimates, these erroneous alignments may result in a large number of false positive splice junction predictions. In this study, we demonstrate how deep learning algorithms can be used to determine the features of splice junction sequences from experimental data. We utilise deep convolutional neural networks for a new splice junction classification tool called DeepSplice, which (i) performs better than the most advanced techniques for splice site prediction, (ii) exhibits great computational efficiency, and (iii) allows users to apply the tool to their own self-defined training data.

3. METHODOLOGY

i) Proposed Work:

The proposed system utilizes Convolutional Neural Networks (CNNs), a deep learning approach that is highly effective in image-based classification tasks. Unlike traditional machine learning algorithms like SVM, Naïve Bayes, and KNN which require manual feature extraction, CNNs automatically learn spatial hierarchies of features from input images. This makes them particularly suitable for medical imaging applications such as mammogram analysis. The network consists of layers of interconnected neurons, where each neuron performs computations and passes data to the next layer. Through layers such as convolution, pooling, and fully connected layers, CNNs are capable of identifying complex patterns associated with breast tumors.

CNNs are inspired by the human visual cortex and are designed to detect image features at different levels of abstraction. In this system, CNN models like MobileNet and Inception V3 are employed to classify breast cancer from mammogram images by extracting deep features directly from the data. These architectures are lightweight and powerful, offering both accuracy and speed. The system aims to determine the most suitable CNN model for breast cancer prediction, ultimately providing better support to radiologists in early diagnosis and improving patient outcomes through efficient and accurate detection.

ii) System Architecture:

The architecture for breast cancer detection using deep learning begins with the input of mammogram images, which are first preprocessed to enhance image quality. This preprocessing step includes resizing images to a standard dimension, removing noise, and normalizing pixel intensity to prepare the images for feature extraction. These processed images are then fed into a Convolutional Neural Network (CNN), which is specifically designed to automatically extract features from visual data. The CNN consists of multiple layers including convolution layers, activation functions (ReLU), pooling layers, and fully connected layers, all working together to capture both low-level and high-level features of the tumor regions.

After the features are extracted, the CNN passes them through a softmax layer that classifies the tumor as either benign (non-cancerous) or malignant (cancerous). The system utilizes advanced CNN models such as MobileNet and Inception V3, which offer high accuracy and performance due to their efficient architecture and ability to learn complex image features. Finally, the output is evaluated using performance metrics such as accuracy, precision, recall, and F1-score to assess how well the system is able to predict breast cancer. This automated architecture not only enhances detection speed but also supports radiologists in making more accurate and reliable diagnoses.

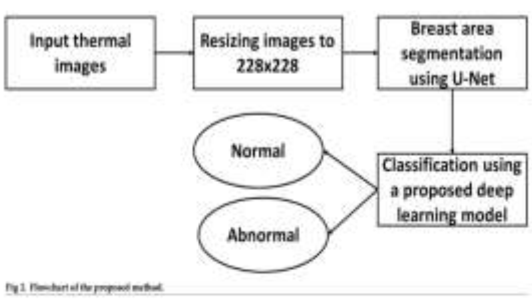

Fig.1. Proposed Architecture

iii) MODULES:

a) Image Acquisition Module

- Collects mammogram images from medical datasets or real-time inputs.
- Converts images into a compatible format for further processing.

b) Preprocessing Module

- Resizes and normalizes images to ensure consistency in input data.
- Enhances contrast and removes noise to improve feature visibility.

c) Feature Extraction Module (CNN Layers)

- Applies convolution and pooling layers to extract important visual patterns.
- Identifies low-level (edges, textures) and high-level (shapes, tumor areas) features.

d) Classification Module

- Utilizes CNN models like MobileNet and Inception V3 to classify images.
- Determines whether the tumor is benign or malignant based on extracted features.

e) Result Prediction Module

- Displays the classification result to the user (Benign/Malignant).
- Shows the confidence score or prediction probability to indicate model certainty.

f) Performance Evaluation Module

- Measures model effectiveness using metrics such as accuracy, precision, and recall.
- Displays the confusion matrix to visualize true vs. predicted classifications.

iv) ALGORITHMS:

a) **CNN** – CNNs, or convolutional neural networks, are widely used. Perhaps the most well-known deep learning architecture is this one. Convnets' widespread awareness and efficacy are the reasons behind the most recent rise in interest in deep learning. AlexNet launched CNN's pastime in 2012, and since then, it has expanded rapidly. Researchers advanced from eight-layer AlexNet to 152-layer ResNet in just three years.

These days, CNN is the go-to mannequin for every issue involving photographs. They completely outperform the rivals in terms of precision. It is also effectively used for herbal language processing, recommender systems, and other applications. CNN's primary advantage over its predecessors is that, aside from human oversight, it automatically recognises the crucial components. For instance, it learns unique characteristics for each category on its own given a large number of images of cats and puppies. CNN also has a high computational efficiency. It performs parameter sharing and utilises unique convolution and pooling algorithms. This makes CNN styles broadly appealing by enabling them to function on any device. This sounds like perfect bliss all around. We are working with a very efficient and eco-friendly mannequin that uses automated feature extraction to achieve superhuman accuracy (yep, CNN models can currently classify photographs more accurately than people). With any luck, this article will help us uncover the methods and mysteries of this amazing technology.

4. EXPERIMENTAL RESULTS

The experimental results of the proposed breast cancer detection system demonstrate the effectiveness of deep learning models, particularly Convolutional Neural Networks (CNNs), in accurately classifying mammogram images. Both MobileNet and Inception V3 architectures were trained and tested on a labeled dataset containing benign and malignant breast tumor images. The models were evaluated using performance metrics such as accuracy, precision, recall, and F1-score. Inception V3 achieved higher accuracy due to its ability to capture multi-scale features, while MobileNet performed efficiently with lower computational cost. The results indicate that the proposed deep learning approach not only improves diagnostic accuracy but also provides faster predictions, supporting radiologists in making reliable decisions for early breast cancer detection.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\, cision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

$$Recall = \frac{TP}{(FN + TP)}$$

mAP: One ranking quality statistic is Mean Average Precision (MAP). It takes into account the quantity of pertinent suggestions and where they are on the list. The arithmetic mean of the Average Precision (AP) at K for each user or query is used to compute MAP at K.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

Fig 2. Upload data

Fig 2. Predicted output

5. CONCLUSION

In this study, we suggested a convolution neural network as a computer-aided diagnostic (CAD) system. In order to distinguish between normal and abnormal mammograms, convolution neural networks are utilised. Early cancer detection and treatment recommendations are always desirable. We are able to diagnose breast cancer with 83% accuracy by utilising the Inception V3 architecture.

6. FUTURE SCOPE

The future scope of breast cancer detection using deep learning holds great potential for further improving diagnostic accuracy and efficiency. One direction for future work is to integrate more advanced CNN architectures, such as ResNet or DenseNet, to further enhance feature extraction and reduce overfitting. Additionally, expanding the dataset to include a wider variety of mammogram images, such as those with different age groups, ethnicities, or breast tissue types, would improve the model's generalization and robustness. Another avenue is to combine multimodal data, such as integrating ultrasound or MRI images with mammograms, to provide a more comprehensive analysis and reduce false positives or negatives. Finally, real-time implementation of these models on mobile or cloud platforms for faster and more accessible diagnosis, especially in remote areas with limited access to medical professionals, could significantly impact global healthcare.

REFERENCES

1. R. L. Siegel, K. D. Miller, and A. Jemal, "Cancer statistics, 2016," CA Cancer J Clin, vol. 66, pp.7-30, 2016.

2. Poorolajal, J., et al., Breast cancer screening (BCS) chart: a basic and preliminary model for making screening mammography more productive and efficient. J Public Health (Oxf), 2017: p. 1-8.

3. Z. Jiao, X. Gao, Y. Wang, and J. Li, "A deep feature based frameworkfor breast masses classification," Journal of Neurocomputing, vol. 197,pp. 221-231, 2016.

4. J. Arevalo, F. A. González, R. Ramos-Pollán, J. Oliveira, and M. A.Lopez, "Representation learning for mammography mass lesion classification with convolutional neural networks," Comput. Methods Program Biomed, vol. 127, pp. 248-257, 2016.

5. Deng, L., Yu, D.: Deep Learning: Methods and Applications. Now publishers, Boston (2014).

6. Krizhevsky, A., I. Sutskever, and G.E. Hinton. Imagenet classification with deep convolutional neural networks. in Advances in neural information processing systems. 2012.

7. Zhang, Y., et al. DeepSplice: Deep classification of novel splice junctions revealed by RNA-seq. in Bioinformatics and Biomedicine (BIBM), 2016 IEEE International Conference on. 2016. IEEE

8. Hua, K.-L., et al., Computer-aided classification of lung nodules on computed tomography images via deep learning technique. OncoTargets and therapy, 2015. 8.

9. Pravin S. Mane, Indra Gupta, M. K. Vasantha , "Implementation of RISC Processor on FPGA", Electrical Engineering Department, Indian Institute of Technology Roorkee, 2006 IEEE.

10. Kui YI, Yue-Hua DING, "32-bit RISC CPU Based on MIPS", International Joint Conference on Artificial Intelligence 2009.

11. Mrs. Rupali S. Balpande, Mrs. Rashmi S. Keote, "Design of FPGA based Instruction Fetch and Decode Module of 32-bit RISC (MIPS) Processor", International Conference on Communication Systems and Network echnologies, 2011.

12. Mr. S. P. Ritpurkar , Prof. M. N. Thakare , Prof. G. D. Korde, "Synthesis and Simulation of a 32Bit MIPS RISC Processor using VHDL", IEEE International Conference on Advances in Engineering & Technology Research, 2014.

13. David A. Patterson, John L. Hennessy, "Computer Organization and Design", the Hardware and Software Interface, Third Edition.

14. J. C. Tobias Charistian Cahoon, Melanie A.Sutton, "Three-class mam mogram classification based on descriptive cnn features," 2000.

15. S. Sharma, M. Kharbanda, and G. Kaushal, "Brain tumor and breast cancer detection using medical images," International Journal of Engi-neering Technology Science and Research, vol. 2, 2015.

16. P. Hankare, K. Shah, D. Nair, and D. Nair, "Breast cancer detection using thermography," Int. Res. J. Eng. Technol, vol. 4, 2016.

17. S. Hwang and H.-E. Kim, "Self-transfer learning for fully weakly supervised object localization," arXiv preprint arXiv:1602.01625, 2016.

18. Z. Mohammadzadeh, R. Safdari, M. Ghazisaeidi, S. Davoodi, and Z. Azadmanjir, "Advances in optimal detection of cancer by image processing; experience with lung and breast cancers," Asian Pacific journal of cancer prevention: APJCP, vol. 16, no. 14, 2015.

Author's Profiles:

Ms. GUNA GAYATHRI PRASEETHA K is currently working as a Assistant Professor in the Department of Computer Science and Engineering at

PBR Visvodaya Institute of Technology and Science, Kavali, SPSR Nellore, Andhra Pradesh, India. She had 6 years of academic experience. She earned master's degree in Computer Science and Engineering. She had Published more than 3 research papers in various International Journals Research areas are Artificial Intelligence and Machine Learning and Blockchain technology.

Email- gayathripk.cse@gmail.com

I am Snehalatha Reddy Chundi, currently pursuing a B. Tech in Computer Science and Engineering at Visvodaya Engineering College, Kavali, SPSR Nellore, Andhra Pradesh, India. My areas of interest include Python, HTML, CSS. I have earned certifications such as NPTEL in 'Social innovation in industry 4.0, 'Dotnet Certificate' from Wipro. I have also completed a Python internship at Codtech It Solutions Pvt. Ltd, where I gained hands-on experience in efficient code, and implementing some projects, which provided hands-on experience and practical skills in realworld projects involving Portfolio using web development, Html, CSS.

I am Maneesha Chilakapati, currently pursuing a B. Tech in Computer Science and Engineering at Visvodaya Engineering College, Kavali, SPSR Nellore, Andhra Pradesh, India. My areas of interest include Python, HTML, CSS. I have earned certificate 'Dotnet Certificate' from Wipro. I have completed a Python internship at Codtech It Solutions Pvt. Ltd, I have also completed a python development internship at Cognifyz Technology Pvt. Ltd. where I gained hands-on experience in efficient code, and implementing some projects, am a proficient developer with expertise in HTML, CSS, and Python, capable of building responsive and dynamic web applications.

I am Yellamchetti Giri, currently pursuing a B. Tech in Computer Science and Engineering at Visvodaya Engineering College, Kavali, SPSR Nellore, Andhra Pradesh, India. My areas of interest include Java, SQL HTML, CSS and Artificial Intelligence. I have earned certifications such as 'Full Stack Development ', 'Build Your Own Generative AI Model'. ‘Young Professional from TCS iON Career Edge’, ’Communication and Team Work' from edX. I have also completed a Python internship at Pantech e learning Pvt. Ltd, 'Java programming' internship at Codtech It Solution Pvt. Ltd. and 'Java Development' at Cognifyz Technologies Pvt. Ltd. I have gained valuable experience and skills through internships and certifications, enhancing their technical expertise in computer science and engineering.

I am Venkatesh Kuthala, currently pursuing a B. Tech in Computer Science and Engineering at Visvodaya Engineering College, Kavali, SPSR Nellore, Andhra Pradesh, India. My areas of interest include Python, Java, SQL, MERN Full Stack Development. I have earned certifications such as NPTEL in 'Entrepreneurship Essentials, 'Java Full Stack' from Wipro, 'MERN Full Stack Development' from Data Valley, ‘Web Development' from Evolution Technology, ‘Network Security Associate Virtual internship' from EduSkills, 'Communication and Team Work' from edX. during my internships I gained hands-on experience and practical skills in real world projects involving Portfolio Website using

Front end technologies, YouTube video downloader application using front end and python, CATAPI using web technologies, Breast cancer detection using deep learning, web technologies and python.