Intelligent Identification of Breast Cancer Empowered with Machine Learning

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# Abstract

Every year many people die due to the late diagnosis of cancer. Early detection of this deadly disease can reduce mortality rates. Breast cancer is one of the significant types of cancer and regularly recognized malignant growth among women and necessary explanation behind expanding death rate among women. The only way to decrease it is to diagnose it at early stages. Diagnostic errors by medical practitioners are considered one of the leading causes of death. The advent of technology has made it easier for humans to automate patient prognosis and reduce disease from symptoms and report analysis. Although modern era technology makes it easy to detect cancers early, much work is still needed in this field. In this research, fusion-based, different machine learning algorithms will apply to diagnose breast cancer early. For this purpose, two datasets (images and Features based) were collected from Kaggle and IEEE-dataport. The proposed model is trained on an image-based dataset using a convolutional neural network. The features dataset is trained using deep extreme machine learning in the proposed fusion-based model, showing better accuracy than the state-of-the-art previous published approaches.

**Keywords:** Artificial Intelligence, Machine Learning, Convolutional Neural Network, Deep Extreme Machine Learning.

# Introduction

Artificial intelligence (AI) is a subfield of computer science. It emphasizes the creation of intelligent machines that work, behave, and react like humans. It has become an essential part of the technology industry nowadays. In recent years, there has been a magnified focus on using artificial intelligence in several domains to resolve complex issues, such as urban infrastructure, resident living environment, transport management, medical treatment, shopping, security assurance, and so forth. Further, the endorsement of artificial intelligence in health care is growing whereas evolving the face of health care delivery.

Early detection of cancer is one of the main approaches to prevent death. Breast cancer is the second-biggest cause of mortality between forty to fifty-five years (Zaheer et al. 2019). Globally, the underlying cause and diagnosis at the initial stage of breast cancer are considered significant problems that drastically affect mental and social dimensions in human life. The medical practitioners recommend several tests to perform. The underlying symptom of breast cancer typically involves forming a lump in the breast or under the armpit; modification, irritation, and dimpling in skin size and nipple become pulled in and reddish in colouration (Momenimovahed and Salehiniya, 2019).

The abnormal development of human cells in an organ is termed tumours that may be cancerous. There are two types of tumours; benign and malignant. Benign tumours are localized, surgically treated, and do not life-threatening, such as fibroids and lipomas. They can only be dangerous when developing in the brain and interacting with any organ's typical structures or block terminals. Besides, various benign tumours like internal organ polyps are precancerous and are surgically eliminated to prevent their transformation into malignant. These tumours generally don’t reappear once eliminated, but they will generally be in the same position (Wan et al. 2016).

Malignant tumours are cancerous and may lead to death if untreated. The tumour cells can invade surrounding tissues or enter the bloodstream or lymph nodes and influence physiological regulations. They can progress in any part of the body, such as the breast, intestines, lungs, reproductive organs, blood, and skin (Schmid et al. 2018).

The mortality rate of breast cancer is remarkably high. As WHO (world health organization) demonstrated, breast cancer is the most frequent cancer among women, and almost 2.1 million women are affected each year. In 2018, around 627,000 women were no more due to breast cancer development (Jafari et al. 2018).

To reduce the diseased state, many experimental procedures are used. Information technology such as data mining and other artificial intelligence approaches such as machine learning, backpropagation neural networks, classification, and support vector machines are used (Khan et al. 2020).

Machine Learning techniques are recently used in various emerging fields of science. Like, medical domain, Smart city, Health, etc. (Kalantari et al. 2018). Machine learning is a subfield of artificial intelligence (AI) where software programs can classify and predict results accurately without programming them explicitly. The learning process of ML software modules involves providing some data for those models, allowing those models to look for patterns into data and make better decisions in the future based on the data provided. The main aim of ML is to enable software programs to be learned directly from provided data and adjust their results according to this data without the aid or interference of humans.

Deep extreme machine learning is a subfield of machine learning. Deep extreme machine learning generally uses sequences of several layers to accomplish the feature extraction and classification tasks. Layers used in deep extreme machine learning are connected in a cascade manner so that the output of each layer is connected to the input of the following layer. With deep extreme machine learning, software modules can be learned and trained to accomplish classification and prediction tasks from images, sounds, videos, or text data. The performance and accuracy of deep extreme machine learning models can be very excellent and exceed human beings' performance. Deep extreme machine learning models are trained to accomplish classification or regression tasks using many datasets (data with labels) and robust neural network structures (Nguyen et al. 2019).

The artificial neural network model is based on various layers that are connected like neurons. An artificial neural network is another subfield of machine learning that is briefly stimulated by the human neural network, and it employs different neurons to perform amassed tasks. Moreover, Deep Neural Network frequently constructs an effective breast cancer disease diagnostics model that provides better data accuracy (Shen et al., 2019).

Late diagnose of breast cancer is one of the leading causes of death. This research proposed an intelligent system that will predict breast cancer empowered with fusion-based machine learning algorithms. For this research, the two different types of datasets (images and Features based) were collected from Kaggle and IEEE-dataport. The proposed model is trained on an image-based dataset using a convolutional neural network and a features dataset trained using deep extreme machine learning.

## Aim(s)

To design an effective and efficient health care model to predict breast cancer disease based on a fused Machine Learning approach.

## Objectives

This research aims to overcome the banking loan defaulter and predict it in the early stages.

* Literature Review work on state of the art and popular approaches already used for breast cancer prediction.
* Analyzing the datasets for better accuracy in minimum time to predict breast cancer in the health care sector.
* Devising a new probabilistic approach fused based model for breast cancer prediction using machine learning.

## Research Questions

The question that motivates the project’s progress forward is as follows:

* What is the significance of predicting breast cancer stages by using a fused Machine Learning model?
* How does the Machine Learning model can help to extend the accuracy of the proposed systems?
* What are the parameters that involve in the evaluation of the breast cancer prediction system?

## Ethical Considerations

Ethics is a complicated subject that has only become more prominent during the advent of Big Data. The UK Data Service department also provides guidelines for ethical research with specific relation to Big Data. These guidelines will form the basis for this report’s ethical approach.

## Project Timeline

This process of assigning deadlines to the modules of the project is called creating a project timeline. A Gantt chart is the tool preferred worldwide to visualize the project timeline. The project timeline for this project is shown in Figure 1.1.

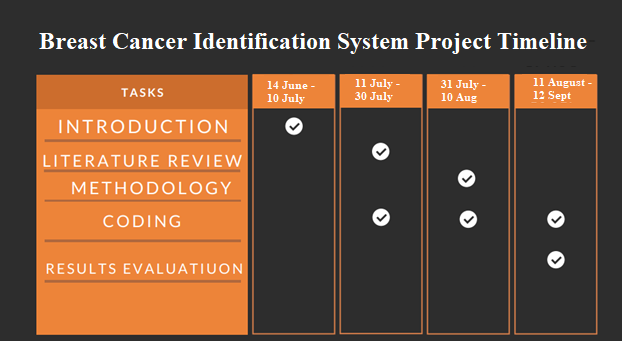


Figure 1.1: Project Timeline for Breast Cancer Prediction System

## Limitations

As indicated by the idea of subject, it is amazingly colossal and as the bosom disease is fundamental sickness over the globe. It is open adequately so there no geographical repressions. It will be an advancement based research as there may be a couple of issues and constraints occurred on programming and gear level. Subject has its own one of a kind hugeness in analyze bosom malignancy and has outstandingly enormous point of confinement. We will research and discussion about different reactions and propose basic response for analyze the bosom malignant growth. We will moreover endorse the results by using some machine learning models or some unique techniques like fusion based model.

# Literature Review

Breast cancer has become one of the most well-known diseases among women in developing countries around the world in the last year, and it has also become a leading cause of mortality. Various pledges have been made in the literature regarding using example pattern recognition algorithms for tissue-level breast tumour conclusions.

A strong Literature Review provides good guidance from the experiences of fellow researchers working in the same domain. It also includes the quality and validation of the research being done. The following papers have been finalized for Literature Review in this Research.

Computer technology is using in every aspect of life as well as the medical field. In the medical field, information technology is using for the diagnosis of diseases. Experience, expertise, and logical ability are essential elements of taking decision support system. The area has highly complex and anomaly where we use computer technology. Fuzzy logic, neural network, and genetic algorithm have been developed to overcome this complexity and irregularity. Haddadnia et al. (2012) used genetic algorithms and artificial neural networks to improve breast cancer diagnosis. They show how they used medical infrared imaging to analyze quantitative and qualitative data to diagnose cancer. The optimum diagnosis parameters are chosen from among the available parameters, and precision in cancer diagnosis is achieved by using genetic algorithms and artificial neural networks.

CAD systems have been used to detect and describe various cancers, including numerous CAD systems specifically built and utilized for breast cancer. CAD is becoming a more critical tool in the mammographic interpretation process to help radiologists reach firm judgments. In clinical practice, current CAD systems act as a second reader for breast cancer detection. Several research groups are working on CAD systems for the classification of malignant and benign lesions.

Computer-aided diagnosis (CAD) is a significant research area in medical imaging (Massion and Walker, 2014). The basic idea of CAD is to use the quantitative output from an algorithm (computer software) as the "second opinion" to assist the radiologist in interpreting tasks related to disease detection (Doi, 2007). CAD has two broad goals: first, to improve the radiologists' reading accuracy and consistency, and second to shorten the image interpretation time. The general design of CAD is to detect (locate) suspect disease regions (e.g., a lesion) in one or several medical imaging modalities/images; and to generate a likelihood score for the presence of a particular disease. These two designs correspond to CAD for disease detection and CAD for differential diagnosis (Doi, 2005).

CAD has been developed in various imaging modalities such as magnetic resonance imaging (MRI), CT, projection radiography, nuclear medicine, ultrasound, and digital pathology imaging; and is used for all parts of the body, including the head, thorax, heart, breast, liver, prostate, and bones. Examples of CAD schemes developed in the past include pathological brain disease detection in MRI (Zhang et al. 2010); (Zhang et al. 2011); (Zhang et al. 2015) detection/diagnosis of breast lesions on mammograms (Gilbert et al. 2008). Typically, each CAD system is tailored for a specific disease and imaging modality. In general, these CADs depend on a conventional machine learning scheme, segmentation of the region of interest, feature extraction, and classification to make the final decision.

Inconspicuous information on a patient's condition, automated clinical diagnosis is a significant field of interest in computer vision. The face, as a reflection of health status, can show symptoms of some diseases. Therefore, identifying facial irregularities or unusual characteristic is of paramount significance once it comes to clinical diagnosis. Computer vision techniques have recently been shown in clinical diagnostics by using face images. Various methods have been considered for assessing facial symptoms and ultimately providing additional assistance to doctors. However, advanced tools are still rarely used in medical training. Their reliability is still an issue because of these methods' lack of medical approval and inadequate application. However, work has been done to offer accurate plans for the health sector by addressing practical problems, including real-time diagnosis and patient placing. The latest set of highly related and advanced solutions has been examined in facial imaging (Thevenot et al., 2017).

Yasmin et al. (2013) employed image processing techniques and algorithms to detect breast tumours and, in some circumstances, assess their stage so that the cancer patient might receive correct treatment to improve his quality of life. For early-stage breast cancer diagnosis, digital mammography is commonly employed. Due to their harmful effects on the human body, various safe approaches such as infrared imaging, MRI, and biopsy are also proposed.

Al-shamlan et al. (2010) advocated extracting feature values from mammography pictures of breast cancer to classify the tumour. They're employed in two different ways. The first step is to increase the image's contrast. Another segmentation approach identifies the location of a mass identification system. They got positive outcomes. The outcomes were the expected reach attributes in every feature extraction.

Maitra et al. (2011) recommended employing a Technique for preparing digital mammography to analyze images. They're used to make computations for PC-assisted locating (CAD). This estimation is utilized to lessen clamour, edge-shadowing impact, accurately perceive pectoral muscle, and sufficiently smother the pectoral muscle without losing any information from the mammogram's straggling leftovers. The resulting mammography can be employed for computerized variants of the standard human bosom discovery, such as calcification, encompassed masses, postulated masses, and other less well-represented groups, delineated injuries, asymmetry evaluation, and so forth. Work on making and smoothing the pectoral muscle segmentation could be coordinated further.

These days, hazardous development is an enormous trendy scientific difficulty all completed. As indicated through the International Agency for Research on Cancer (IARC), a few pieces of the World Health Organization (WHO), there were 8.2 million passing performed by compromising development in 2012, and 27 million of latest activities of this disorder are relied on to take place until 2030.

(Jones et al. 2003) noticed that malignancy, restoratively described as a compromising neoplasm, is a broad gathering of pollution which remembers unregulated cell improvement for infection; cell isolates and turns out to be uncontrollably surrounding dangerous tumours, assaulting near to added substances of the casing. The threatening development can unfurl to all segments of the edge through the lymphatic structures or circulatory frameworks.

(Laé et al. 2007) pointed out disease can be analyzed by arranging tumours in two unique sorts: threatening and favourable. Favourable tumours speak to a queer protuberance yet seldom escort to a sufferer's passing; yet, a few kinds of human tumours, as well, can build the chance of creating disease. Then again, dangerous tumours are more genuine, and their reasonable conclusion adds to a fruitful treatment. Subsequently, prediction and decision of malignant growth can help the odds of treatment, diminishing the generally significant expenses of clinical methods for such patients.

(Agrawal, 2014) stated that Bosom malignancy (BM) is the most often analyzed disease and the maximum broadly identified motive for loss of life in ladies anywhere in the route of the globe. Amid the malignancy types, BC is the second maximum number one disease for women, barring skin disorder. In addition, the mortality of BC is alternatively immoderate while contrasted with particular varieties of the malignant boom. BC, like extraordinary tumours, begins with a brief and managed outgrowth and boom of a piece of the bosom tissue, which depending upon its possible damage, is separated into the type and harmful kinds. By and massive, there are types of Breast Cancer that may be in the scenario and obvious. In-state affairs start in the milk conductor and do not spread to various organs regardless of whether or not creates. Prominent chest-threatening development, notwithstanding what is most likely expected, is robust and extends to multiple closes by organs and wrecks them as well. It is essential to developing to know about the risky cell sooner than it spreads to exact organs; like this, the continuance expense for the influenced character will require augmentation to in extra of 97 percent. Decent estimated greatness of issues in innovative clinical information incorporates the assessment of pollution due to different checks completed upon the influenced individual. The appraisal of data taken from patients' and experts' choices is the greatest significant factor in finding. The correct examination of breast cancer is one of the severe issues inside the clinical order. As BC might be unmistakably intense, early fame can stop mortality. The clinical surrender of BC encourages anticipating the compromising cases and helpful devotion to expand an influenced character's fate rates from 56 to 86 percent.

(Nyström et al. 2002) bosom Cancer has four early symptoms: microcalcification, mass, constructing mutilation, and chest asymmetries. The exceptional everyday strategies used for dangerous chest development coming across (BCD) are positron unfold tomography (PET), desirable resonation imaging (MRI), CT channel, X-shaft, ultrasound, photoacoustic imaging, tomography, diffuse optical tomography, elastography, electrical impedance tomography, optoacoustic imaging, ophthalmology, mammogram, and many others. The effects of these tactics are used to look at the models, hoping to assist the masters in masterminding the unstable and kind cases.

(Spanhol et al. 2017) explored that Dismissing late advances in the comprehension of the nuclear look at BC development and the disclosure of recent associated sub-nuclear markers, the histopathological assessment stays the maximum considerably used Technique for BC finding. Notwithstanding significant progression came to by way of suggestive imaging advancements, the ultimate BCD, including exploring and masterminding, maintains being finished through pathologists applying visual assessment of histological models beneath the amplifying focal point, in any case, the manual portrayal of photos is a challenging and monotonous project, being especially unprotected to bury onlooker irregularity and human goofs, achieving helpless essential results, as such incredibly extending the rest of a load of radiologists because of their substantial lack. Additionally, clinical concept charges which are suitable for imaging hastily increase. As wishes are, new methods for warranty are required. At present, bioimaging assessment is a rising technique within radiology with growing implantation in centre core interests. It gives relevant facts that aren't always clean via the independent eye in standard radiological scrutinizing. It includes the length of quantitative (mathematical) facts from photos, typically of huge preferred, to provide statistics to aid a medical evaluation. Biomarkers can be the change from radiology to personalize prescriptions.

Majid et al. (2020) suggested a model that distinguishes gastric infections through multi-type features extraction, fusion, and vigorous features extraction. Kvasir and Private Datasets were used to develop a database for tests. The dataset consisted of five classes, four the infected ones, and one healthy class. Three types of features discrete cosine transform (DCT), discrete wavelet transform (DWT), and strong color features (SCFs) were extracted in the suggested model. The maximum accuracy reached by the model is 96.5%.

Khan et al. (2020) recommended a hierarchical framework of SVM and CNN for brain tumor segmentation. The suggested model comprised two segments. First Confidence surface modality (CSM) generation and brain tumor segmentation using CNN. CSM generation phase comprising six steps including MRI fusion, pre-processing, feature selection, feature extraction, feature labeling, and classifier training. In the second phase, the proposed CNN architecture took the input of 2D extracted regions from the first phase. The CNN model recommended by the researcher comprises further three pathways (TP) to retrieve a different level of features at every step. Each pathway processed the 2D image extracted from the respective modality and then the feature maps were combined. Dice Similarity Score was applied to calculate the system's accuracy and the BRATS-2015 dataset was used. The novel TP-CNN model achieved 0.81 on the complete tumor, 0.76 on the core tumor, and 0.73 on enhancing tumor.

Machine learning (ML) is a branch of Artificial Intelligence (AI) in which statistical techniques are used to give computer systems the ability to "learn" and improve on their own without having to be explicitly programmed.

The tremendous amount of data available in modern times is impossible for humans to keep up with and understand. Machine learning, a discipline of artificial intelligence subset of computer science, focuses on developing and implementing algorithms to solve this challenge. Recent advances in this discipline have opened up wide and nearly unlimited possibilities in fields ranging from finance to data security to medicine. However, there is still much room for advancement in social media services, disease prediction and identification, virtual assistants, search engine refinement, fraud detection, manufacturing, and other areas where Machine Learning can be used. It will only develop and integrate into our daily lives in the future, making things more accessible and more convenient.

Machine learning entails the research and development of algorithms that can learn from and predict data and datasets using various teaching processes (Lee et al., 2017). Machine learning is a process of data discipline that gives computers the skill for learning deprived of being encoded with clear rules. The design of procedures that can absorb and make accurate and relevant guesses are enabled by Machine learning. Machine learning benefits from more significant exposure to bulky and novel data sets and can progress and acquire with experiences instead of rule-based algorithms. New developments within machine learning provide potential in many fields and applications, with computed tomography. Machine learning is a course of techniques and research areas that allow computers to understand like hominids and make them able to outline or organize configurations. Technologies may be more reliable to analyze data further, and snippet features from data that humans cannot do. It is known that there are types of machine learning, and these types work with multiple techniques to solve numerous scientific problems. These important categories of machine learning can be described as follows: Supervised machine learning, Semi-supervised machine learning, unsupervised machine learning, and Reinforcement learning.

CNN's deep architecture has effectively provided excellent efficiency to trained models by learning patterns through raw images. Inception is a proposed deep neural network architecture, which attains the ILSVRC2014 (Image Net Large-Scale Visual Recognition Challenge 2014) assessment and the new architecture for identification. The primary goal of the design is to make better use of computing resources within the network. Through careful design, the depth and breadth of the network are increased when maintaining a computational and financial plan (Szegedy et al., 2015).

Hamet et al. (2018) proposed Artificial Intelligence (AI), a broad term that uses a computer to simulate intelligent behaviours with little or no human interaction. It is widely assumed that AI began with the development of robotics. The term comes from the Czech word machine, which means forced labour with biosynthetic machines. The expanding use of robotic-assisted surgery, named after Leonardo Da Vinci, for a complex urologic and gynecologic process is today's lasting legacy in this profession. Da Vinci's robot sketchbooks paved the way for this breakthrough. In 1956, AI was formally established as the science and engineering of creating intelligent machines. The phrase refers to a wide range of medical topics, including medical statistics, medical diagnosis, robotics, and human biology, including today's Omics technology. The two main fields of AI in medicine, which are the focus of these views, are physical and virtual. The virtual branch encompasses information systems ranging from deep learning data management to health management system control, active physician guidance, and electronic health records in treatment decisions. Robots that aid the elder sufferer or the attendant surgeon best reflect the physical branch. Targeted Nanorobots, a novel new medicine delivery device, is also included in this field. These applications' societal and ethical complexity necessitate more thought, demonstrating their economic worth, medical utility, and the development of multidisciplinary methods for their essential use.

Willis et al. (2019) focused on a familiar expert's record about sufferers' dispassionate experience and searched whereby those chores proceedings accommodate computerized technology through artificial intelligence. It is intelligent technology one now taking a human languages conversation among more than one individual. Using a conversation identifier technique can upgrade the sufferer and giver conversation in word format transcription. Adopting NLP, these words could be more decreased along explicate to deliver medically related details this check the method giver rewrites and classified through earlier noticed part of clinical documentation. To figure out all-around performance inside aggregate and quick step dispassionate atmosphere employed experimental research and development well organized speculative information. The concentration of research and development was to figure outplaced effort process of any professional kind on every underlying responsibility from considering massive search work. The review of every profession does not signify any faculty representative within the system, although the domain on this system.

Huang et al. (2018), the purpose of research evolved a resolution known as "Smart Wireless Interactive Healthcare System" (SWITCH) simplify information greeting and communication in a particular era technique to web server secured by cryptography for more search of data elicitation. SWITCHes are along with two major parts: a collective hypertext-based indicator panel and a phone application. As touch mobile has immediately boost dominant reputation, mobile applications are helping everyone in fitness as mediate to hold on the pathway of foodstuff, activeness in addition to heaviness, and that is suspect also systematic than commit on user's automatic description quantum, for mass administration. An artificial intelligence mechanical fitness interactive agent impulse indoors SWITCHes application. The SWITCHes placed analytical testing is fit to be accomplishing behind access Institutional Review Board (IRB) confirmation. The resulted search gives out a review of the progress and accomplishment of SWITCHes.

Mohamed (2020), in this paper, briefly discussed what IoT is, what AI is, the Algorithm of AI, the Challenge of AI with IoT, application of artificial intelligence systems within IoT. In Artificial Intelligence internet of thing Structure, the self-organizing networks and intangible devices illustrate networks are a partition of significant limitations. The networks of tangible commodities are the Internet of things (IoT). A much understandable IoT method may consist of self-organizing networks, and intangible device illustrates networks. The self-organizing networks encourage to upgrade of the networks since high digital communication as long as acknowledgement. The Self-organizing networks may be accomplished spontaneously via an Ethernet and network boost the modem worktable. The networks are figure out as well as describes the shortened way for the information along with issues. AI and IoT both have challenges; when we merge these technologies, challenges become more complex; some of those questions are Protection, Rapport and Complicatedness, Intellectual Absurdity, Pessimism, Cloud Attacks, Technologies and Attacks on Cloud. Applications of artificial intelligence systems in the IoT are home automation, oil field production and smart hotel. Artificial intelligence assigned text determines the retrieve as the research and architecture of interactive agent where interactive agents recognize its atmosphere and get behaviour that increases the possibility of favourable outcomes.

Mohanta et al. (2019) the proposed work describes healthcare5.0 modelling the mainframe of reference. Its important specification is Artificial Intelligence entrenched appliances such as a robotic attendant, automatic Internet of things instruments introduce 5G telecommunication service. It contains individual tools information direction, M2M/D2D, mechanical artificial body-born computing, mobile sensor, microcell, evolved NodeB, utility storage device or healthcare information system, Internet of things based healthcare scheme and emergency warning system. It recommended the conception of secure communication in the intelligent grid, i.e. 5G telecommunication service, which is beneficial to screen all regions of several scopes along with regular digital communication along immense driver assistance system enriching power competence as well as standard of utilities, time-limited resource scheduling and most extended battery life. The viable resolution required a 5G telecommunication service like it provides hardware and software resource to any network. Proposed work encapsulates each essential perspective, such as the Internet of things, artificial intelligence and fifth-generation telecommunication, to the healthcare model version 5.0.

Cáceres et al. (2018) recommended the Intelligence service along the Autonomous approach familiarized from utilization dependent job. The prospect based on Internet of Thing (IoT) along Industrial Internet of Things (IIoT) utilized within the reproduction, like that is represented within those research tasks adopting Discrete Event Simulation (DES), permitting the feasibility to mock up genuine resolutions beyond the execution to bright connected things, developing doable the feasibility atmosphere to check smart rules and regulation depend on Internet of things (IoT) catch information. Inventing and introducing a system for the performance and suggestions of hospitals smart, catching an essential acute care hospital. The recommendations depend on the search analysis of innovative healthcare technology, concentrating toward the sufferer direction. The use of the DES system permits a multiscale modelling system about refurbishing method and detects system congestion. This congestion is enhanced through the extension of wearable devices put into action in Discrete Event Simulation technology. These help to better the sufferer direction assemblage along with utility aspects. In the emergency department, it precisely affects the devaluation of fatality. The formation of robots and other recent automation within the electronic atmosphere adopting this feasibility method, although the structure is suggested like a hypothetical system. The multi agent-systems based imitations are an opportunity to mimic and check from deeply the conceptual associated wearable device of much sensible along controller atmosphere.

Oh et al., (2019) the goal of the study to propose a cloud hospital management software to permit little and mid-sized hospitals to supply small emergency rooms or advanced modernized repetitiveness. The search was attending in cloud competing placed assistance, (PBR) Personal Biological record, (EMR) Mobile electronic medical record utilities, assistance or health-farm ample information supply. The search tested to the allotment as improve adoption's puff measure automation into emergency rooms parts. On the assumption that facilities suppliers may contribute cost-effective, well-being standers deafening health-farm assistance, the like benefits supplies set off large to the stipulation despite the obstruction. Firstly, the investigation results show this expansion as puff vault circle or meshwork transmission capacity grants other end-users to come about maintained. Secondly, this is launch alike package bulk has a small as not at all effect as structure presentation. Thirdly, this is established like puff-build disperse vault together with dispose of were also productive that Appling browser-based bibliography on condition as converting a considerable number of information. The structure is shown profitable dominance add join split lead's funds along with reducing price, authorized problem solving-time change an emergency room information, also advocate as it corporate skill shared as more considerable Health care assistance.

Li (2019), in a proposed research study, machine learning algorithms function in knowledge discovery in data. The mobile digital computer facilitates the terminals that are outdoor of global system for mobile communication networks are settled Moreover efficiently, positioning algorithm divided into three stages is demonstrated and whichever essentially enhanced the positioning efficiency along with acceleration. Knowledge discovery in data has two particular algorithms as statistical and machine learning. The first algorithm used to segregate and anticipation scrutinize correlation and clustering search to implement the procedure. Secondly, the algorithm used AI automation to spontaneously discover prescribed design and specification afterwards discipline and information lots of sampling units. The classification of knowledge discovery in data workload primarily involves regression and classification study, clustering and association rules. The legislator algorithms contain the k neighbour method, support vector machine, neural network, decision tree, Bayesian estimation, etc. This is an essential technique to resolve the issues of knowledge discovery in data. The usual procedure turns out that the positioning strategy depends on machine learning, essentially boosts positioning efficiency and decreases the computational complexity.

Yan (2018) this research described recently, there has been a spike in conversational studies, particularly in the open domain chit-chat research. Our research group is always working on the most intriguing and complex aspects of casual systems. Academic conferences, in particular, are adding new study tracks for informal studies and attracting unanticipated development in the number. There are many submissions to these tracks, and the industry is putting a lot of effort into developing conversational products. In the AI period, the massive mini-scope data is becoming more accessible, and learning technique is becoming much more effective. More advanced informal systems (social chatbots or virtual assistants) may be on the verge of success. Despite the challenges of improving human-computer talks, there is reason to be optimistic about the future of conversational AI if more resources are invested in this field. While most available metrics evaluate created sentences by measuring word overlap and referring to ground truth sentences, automatic evaluation is critical for language creation tasks. Systems that rely on retrieval represent the mainstream chatbot systems in the industry for real-world applications because humans write the responses. Because the sentences are fluent and genuine, they are considered reliable in practice. A massive database with a high number of utterance pairings is essential for success.

He et al. (2019) proposed that many industries, including healthcare, have lately undergone a period of rapid expansion due to artificial intelligence. AI has been used in studies across a variety of medical professions to replicate clinicians' patients diagnosed. The goal is that AI can help people improve their abilities to give Health. Even though such innovations have been continuously evolving, their adoption in diagnosis contexts is still limited. This article looks at some of the most critical issues regarding introducing AI-based technology in healthcare. Artificial intelligence could also be used to replace humans. Whereas AI is improbable to substitute healthcare professionals, it may execute some activities more consistently, quickly, and consistently unlike individuals. For instance, diagnostic tests can be used to estimate bone age, molecular diagnostic scanning can be used to diagnose curable eye illnesses, and cardiology ultrasound can quantify artery stenosis and other measures. Health professionals may also be enabled to handle highly complicated activities by automated jobs that are not technically difficult. Still, it can be highly positive as well as negative and time-intensive. This is enhanced use of human capital. Probably AI's most excellent potent function is as a complement to or improvement of social services. When health professionals and Artificial intelligence perform together, analyses have shown that the results are better than if they worked alone. Artificial intelligence technology may potentially boost actual medical decisions assistance, leading to improved clinical research initiatives.

Deep learning has supported the purpose of Computer Vision in recognizing and classifying images, and it is an essential tool for automating tasks in daily lives. Object identification, classification, and segmentation have been developed using convolutional networks. Because of its ability to learn to represent data, using the convolutional neural network (CNN) on medical images has dramatically helped the medical field (LeCun et al., 2015).

Patel et al. (2012) proposed employing image enhancement techniques to detect breast cancer in mammographic pictures. Different methods, such as frequency domain and spatial domain, are used in enhancement algorithms. The effect of a recurrence space smoothing-sharpening system is investigated to improve mammography image support. They hired a Gabor filter and a contrast enhancement technique. To find good photos, the Gabor filter is utilized. They used the mammography picture to find different filter values than when using the PSNR technique, resulting in superior numerical numbers. The resulting images revealed additional locations that may be used for expressive redirection. Combining Gabor figuring with rapid Fourier change and overlay cover division showed successful ways for removing noise and updating edges, boosting the sign to-commotion extent. Compared to other methods, the superimposition of images transformed using various techniques into a single image inside indicated profitably improved perceive ability and facilitated the ID of good info to the human eye.

Emmanouil et al. (2004) advocated using wavelet-based processing and histogram levelling to improve mammographic images. This study aimed to see how successful the wavelet transform was by using a sigmoid function to process the discrete wavelet transform (DWT) detail coefficients and Histogram Equalization Mapping Functions (HEMF). They upgraded the photos using the six parameters and discovered that the overall image quality was 91 percent. The sigmoid wavelet-based channel provided the superior perception of the bosom skin, thoracic muscle, capillaries, veins, and tracks. Simultaneously, it improved the separation of the average visual representation.

The (SML) Supervised Machine Learning explores algorithms that cause outwardly delivered cases to make overall assumptions, making calculations about upcoming issues. Most intelligent systems frequently use supervised classification. Algorithms like Linear Classifiers, (LR) Logistical Regression, Perceptron, NB Classifier, Support Vector Machine; Quadratic Classifiers, Boosting, Random Forest; and Neural networks algorithm are used where supervised machine learning deals with more classification (Osisanwo et al. 2017).

The approach for mass recognition on digital mammograms was proposed by Martins et al. (2009). They used a K-means bunching algorithm and a dim level co-event grid to depict and break down the surface of divided structures in the image. These structures were grouped using Support Vector Machines (SVM), separating them into two groups based on shape and composition descriptors, masses and non-masses. The accuracy of the arrangement obtained from such a system was 85 percent.

Sampaio et al. (2011) proposed employing CNN, geostatistical functions, and SVM to detect masses in mammography images. This project shows a computer approach that aids in recognition of bosom masses in mammography images. The method's initial phase is to improve the mammography image. This step entails emptying dissents outside the bosom, reducing agitation, and emphasizing the breast's internal components. The regions that may contain masses are then divided using neural cell frameworks. Shape descriptors (uncommonness, circularity, thickness, indirect divergence, and round thickness) are used to investigate these areas' shapes, and geostatistical capacities are used to differentiate their arrangements. Bolster vector machines classify candidate regions as masses or non-masses, with an affectability of 80%, 0.84 false positives and 0.2 false negatives per picture, and a 0.87 area under the ROC bend.

Moradmand et al. (2011) used multiresolution representation to offer a statistical-based feature extraction method for breast cancer diagnosis in digital mammograms. Multiresolution illustrations, wavelet, and curvelet transforms are all used. In light of the quantitative t-test strategy, a highlight extraction technique is developed. As seen by its capacity to separate the classes, the framework positions the elements (segments). A dynamic maximum is then combined with better highlights to get the optimum characterization accuracy (exactness) rate. The order rate for game plans is improving. A support vector machine (SVM) orchestrates normal and pathological tissues and detects benign and malignant tumours. To distinguish between normal and abnormal, the gathering arrangement rate rises to 95.98 percent, and to determine if the tumour is benign or malignant, it rises to 97.30 percent.

Rejani and Selvi (2009) provide research on a mammogram-based tumour identification method. The proposed system is designed to address two issues. One is recognizing tumours as suspicious regions with low contrast against their backdrop, and another is extracting attributes that characterize tumours. The tumour identification approach involves mammography enhancement, tumour area segmentation, element extraction from the segmented tumour region, and the use of an SVM (Support Vector Machine) classifier.

(Keerthana and Xavier 2018) applied Intensity-based Segmentation, and then the implementation of characteristic evolvement was implemented using Gray Level Co-occurrence Matrix (GLCM). GLCM works on the grey level image pixels and extracts 13 properties used in classification later. Support Vector Machine works by creating a hyperplane, and the selection of a hyperplane depends on the kernel. The proposed model consisted of three classes for classification: expected, benign, and malignant, respectively. A Genetic algorithm (GA) was used for making the performance of sort better through SVM. The Genetic Algorithm increased the learning capacity and decision-making of SVM. GA-SVM performed better in the category of MRIs of the brain.

(Vickers, 2017) combined Particle Swarm Optimization (PSO) with Local Binary Pattern (LBP) to efficiently detect brain tumours. In the preliminary stage, Brain Surface Extraction (BSE) was applied for skull removal. As the brain tumour is any irregularity in the normal brain, PSO was utilized to partition the particular area of the BT. Fine-tuned Capsule Network was then used to evaluate the extracted features in previous steps. Feature Extraction was done using LBP, and then the Genetic Algorithm (GA) was utilized for Character Choice. A Capsule setup was used in the last step for tumour detection.

(Abdalla et al. 2019) proposed that the combination of principal component analysis (PCA) and probabilistic neural network (PNN) could be a good classifier in tumor detection. In the initial step, the image data was obtained from the MRIs, and in the advanced processing phase, the pictures were converted into Greyscale and resized into 256 x 256. Character evolvement was done using the principal component analysis (PCA). After the Character Evolvement, the classification was performed using the probabilistic neural network. The outcome of the model was either normal, benign, or malignant. This outcome was analyzed in the analysis phase. The sensitive and specific data were used for accurate classification.

Artificial Neural Network (ANN) is a form of artificial intelligence that has been broadly used to resolve several medical problems. It's been used in various applications, including diagnostics, assessment, image analysis, etc.

(Bimenyimana et al. 2014) described that ANN is another model of machine learning (ML). The development of Artificial Neural Network is inspired by the biological neuron system so simulate the structure and base of functionally like a human brain. As per the name of Artificial Neural Network, it is a combination of three different words. The first is Artificial, which is defined as presenting a real object or some time called human-made and its function is close to that original object. Second neural is an adjective of neurons. Initially taken from the human brain, billions of cells called neurons fundamentally work like biological neurons. Many researchers and developers have used alternative words like connection base network, parallel distributed processing network, etc.

Third, the last word is a network. When using the word network in ANN, we will use different graph structures (directed graph structure) with labelled weight (values), use some connected nodes, and apply some computation operation. It means that every neuron/node is connected simulated to the human brain and works to gather. The Artificial Neural Network is the processing based on an algorithm that can build complex patterns to predict or provide the solution problem.

The similarity between Artificial Neural Network and Biological Brain or Neuron System, to know about the functionality of ANN must be needed to understand how BNS work because the idea of ANN techniques is originated from Biological Brain/Neuron. Many problems were solved on ANN. It is very suitable and efficient for those problem solvers who want to get significant advantages such as cost, ease of debugging/maintenance, accuracy, time, and many more.

There is another advantage of ANN to solve the problem by using the lookup table approach. Fundamentally lookup table is used to store all the information for gaining the appropriate result and reference of upcoming events and through a lookup table approach to generalize the data. In this generalization, ANN will be trained to provide a reasonable solution to the required problem, and ANN trains through many inputs according to the problem we face. After the training section solution may not be satisfied if the given query is not matched with the training section. Another significant advantage of ANN is the memory distributed for large problems or components used within the network.

For mammography images, Sundaram et al. (2012) worked on Histogram Modified Local Contrast Enhancement. They employed a variety of improvement strategies to get various effects and adjust the local histogram. The contrast change for mammography images is shown. The proposed technique improves the distinction of data mammography pictures and protects the information they contain. The test results are also more practical without sacrificing excellence and intriguing information. It employs the information histogram, which essentially does not alter. There are no relics in the yield of the proposed endeavour. The proposed approach is better suited to a wide range of mammography images, including greasy, greasy glandular, and thick glandular images. For each of the 22 amounts of Mias mammography photographs with microcalcification, its execution is examined.

Furthermore, the subjective and target measures are reassuring. This work might be linked to a test of its use for mammography images taken in the presence of noise, and this approach could help distinguish microcalcification in mammograms. Microcalcifications in mammography images have become more visible because of the proposed framework.

Quantum and impulse noise filtering from breast mammography pictures, according to Naveed et al. (2012), utilized two modules: noise detection and noise filtering. The neural network is used for discovery purposes, and it successfully distinguishes noise from images that are severely distorted. Quantum commotion has been observed in mammography images, and the proposed approach has been tested on salt and pepper. The suggested framework is compared to several existing systems using the peak sign to clamour percentage (PSNR) and the critical comparability list measure (SSIM). Analyses reveal that the suggested framework produces better outcomes than existing procedures because it stands out.

Using simple algorithms, Maitra et al. (2011) suggested a method for detecting abnormal growth of masses in the breast. Digital mammography diagnostic is one of the most advanced methods for detecting breast cancer nowadays. Their paper describes a way for creating a supporting tool that will enable detecting suspicious masses in digital mammography images more accessible and faster. Forming homogeneous blocks and colour quantization after preprocessing are the two aspects of the identification procedure. After the suggested approach is applied to raw mammography to discover anomalies earlier, the form and distribution of masses, the size of groups, the type of masses, the direction of masses, and the symmetry between two pairs are cited.

In contrast, representation learning is a class of methods that automatically discover the optimal representation of the raw data and derived features to facilitate classification/prediction/detection (Bengio et al., 2013). Deep learning is a representation learning method that attempts to transform raw data into hierarchical representations by composing multiple levels of nonlinear processing modules (Bengio, 2009). The key aspect of deep learning is that these multiple layers of features are learned from raw data using a general-purpose learning procedure instead of being designed in a handcrafted fashion by engineers. Deep learning methods have been applied to various detection and classification tasks. They have significantly improved the state-of-the-art in multiple domains, such as speech and signal recognition (Dahl et al. 2010), object recognition (Krizhevsky et al. 2012), and natural language processing (Mikolov, 2011). This success also demonstrates that the adaptive representation learning ability is better able to capture and extract the intricate structures in high-dimensional data relative to traditional feature engineering. Deep learning may achieve more success in the future because it requires less engineering by hand.

These days hazardous development is an enormous trendy scientific difficulty all completed. As indicated through the International Agency for Research on Cancer (IARC) is the part of the World Health Organization (WHO), there were 8.2 million passing's performed by compromising development in 2012, and 27 million of the latest activities of this disorder are relied on to take place until 2030.

(Berbar, 2018) were focused on methods of feature extraction to diagnose the malignant masses in mammograms and classify them. They worked to enhance the performance of the GLCM method by introducing seven texture features and applied them on sub-images. By merging two different components, they proposed three hybrid methods; Wavelet-CT1,-CT2, and ST-GLCM. They suggested that all these methods outperform compared previous feature extraction methods according to the AUC measure. They concluded that the GLCM or ST-GLCM extracted a small number of features relative to multiresolution parts.

(Aliev et al. 2017) explored the use of neural techniques to determine heart activity and ensure their outcomes using smart devices. They strongly recommended the use of the neural approach in the field of medical diagnosis.

(Khan et al. 2020) proposed a cloud-based intelligent BCP-T1F and BCP-SVM expert system that specifically diagnoses the breast cancer stage and type of infected person. The expert system will elaborate on the grievous stages of cancer, to which extent a patient has suffered or not. This BCP-SVM system gives the higher precision 97.06 % of the breast cancer detection model, and the BCP-T1F expert system provides 96.56% accuracy of breast cancer at an initial stage.

Another study introduced a technique for the classification of mammograms which was consisted of 4 stages. The preprocessing phase was applied in the median filter to upgrade the picture's nature and exclude clamour in the image. They analyzed the difference in the average of the mammograms and explored the artificial neural network classifier to group the image into a fitting class. The outcome of sensitiveness, particularity, and exactness activity in their model were 72.72%, 93.6%, and 88.66%, respectively (Hamad et al. 2018).

(Chiao et al. 2019) proposed a methodology for detecting breast cancer using a convolutional neural network. A convolutional neural network is utilized to make a short explanation and diagnose breast malignancy disease in many systems that have been established to recognize breast malignancy.

Identifying breast cancer at early stages is an effective way to decrease the associated mortality rate. Specialized radiologists often misconduct the examination or misinterpreted the vital information related to the diagnosis (Muramatsu et al. 2016).

Various deep learning methods have been proposed, including deep belief networks (Hinto et al. 2006), deep Boltzmann machines (Salakhutdinov and Larochelle, 2010), recurrent neural networks (Zhang et al. 2013), and convolutional neural networks (Krizhevsky et al. 2012).

Supervised learning refers to inferring functions from labelled training data (Schapire and Freund, 2012). For example, suppose we want to build a system to classify images that contain dogs or cats. We would first collect a set of labelled images containing dogs or cats. The system will read each image and output two classification scores, one for each category. We tune the system to produce the highest classification score during training when it correctly categorizes the image. This training is performed by iteratively minimizing a loss function to adjust the weights of the deep learning system via gradient descent optimization and backpropagation.

Deep learning techniques have succeeded in object detection tasks of natural images and applied to various medical image analysis tasks. But a significant challenge in the clinical domain is the availability of labelled datasets. For raw image recognition tasks, much of the success comes from access to copious amounts of labelled training data (e.g., millions of tagged images), which enable the training of complicated and deep neural networks with millions of parameters. The amount of labelled training data in the medical domain is much smaller (e.g., hundreds of medical imaging scans). Another issue in clinical imaging applications is the 3D structure of most medical images. A typical magnetic resonance imaging (MRI) or CT scan contains multiple slices, with disease regions inside the scan relatively small compared to the whole image stack (and of varying 3D size). Since cross-sectional imaging slice thickness is always much larger than the in-plane pixel size, capturing 3D information in a deep neural network design is complex.

Several studies have used deep learning techniques to detect/segment abnormal disease regions on 2D medical images. (Su et al. 2015) applied a CNN to segment breast cancer regions in histological images. Similarly (Cruz-Roa et al. 2014) also employed a CNN to detect invasive ductal carcinoma tissue regions in whole slide images. They proposed a CNN-based deep learning architecture to detect basal-cell carcinoma in digital pathology images. (Ciresan et al. 2012) applied similar techniques to train a CNN to segment neuronal membranes in electron microscopy images. Large numbers of 2D training data were obtained in these studies by randomly cropping the large digital images into small patches, and each patch is considered a training sample. (Ronneberger et al. 2015) proposed a U-net architecture for the segmentation of neuronal structures in electron microscopic stacks. This method was composed of a fully convolutional network followed by an up-sampling system to increase the image size. Skip-connections were employed to connect opposing contracting and expanding convolutional layers directly.

(Yu et al. 2017) proposed a volumetric convolutional neural network with mixed residual connections to automatically segment the prostate in 3D MRI studies. The combination of residual connections is employed to improve the network's training efficiency and discriminative capability using both local and global information.

Previous studies have shown that more research is needed to increase early breast cancer diagnosis accuracy using a realistic mammography dataset.

# Methodology

The proposed model of predicting breast cancer using fused based machine learning model will explain in this section. Breast most cancers are the most painful sickness for women in the entire globe. Mostly we used mammography to come across the presence of breast cancer. But I have got different methods to discover this disorder with the aid of only artificial intelligence methods.

Artificial intelligence plays a vital role in every field of life, and computer intelligence's rapid growth has transformed into the digital world. In the Intelligent Health care system, early diagnosis of diseases can decrease the death rate worldwide. The proposed model consisted of fusion-based machine learning techniques.

The proposed model will collect data from two sources: medical examination and electronic medical record, shown in Figure 3.1. The data fusion approach will apply to the medical examination dataset and medical examination data stored in a big database using different sensors. On the other hand, EMR data is also stored in a big database. In the next step, the data fusion approach will apply to different data types like structured and unstructured.

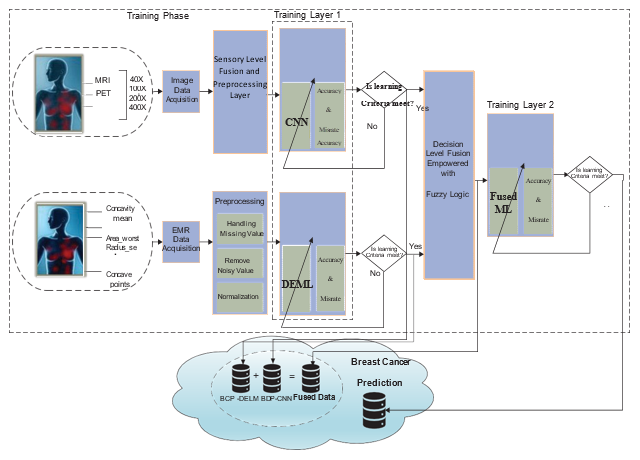


Figure 3.1: Proposed Model for Breast Cancer Prediction System

The preprocessing layer activates and mitigates the noise as well as missing values using the moving average method. ML approaches will apply for the prediction of disease. If the results show positive, then refer to Hospital for further treatment, and if the results show negative, then no disease is detected. In both cases, the data is stored in big data.

The proposed model consisted of two phases training and validation. In the training phase, medical examination and electronic medical records will collect data to detect diseases. Various smart city devices like IoMT will collect data in the form of images using different sensors. In IoT, electronic medical records will obtain in the form of text. Data obtained from IoMT is called unstructured, and data obtained from IoT is called structured data. Pre-processing handles the noise removal and resizing images, and the Data fusion approach technique will apply to structured and unstructured data in structured data. There are further two layers named training layer one and training layer two. In training layer 1, there are two sub-layers, namely the application layer and the performance layer. Machine learning techniques will apply to predicting disease and performance layers to evaluate the proposed model's performance. If the learning criteria don’t perform well, the model needs to retrain. Otherwise, the following training layer 2 activates for predicting disease stages and data stored in the cloud to predict diseases. In training layer 2, machine learning techniques will apply to data for predicting disease stages. A performance layer is used to evaluate the proposed model's performance using statistical parameters like accuracy and miss rate. If the learning criteria don’t perform well, the model needs to retrain. Otherwise, the data will store in the cloud for the prediction of disease stages.

In the validation phase, IoMT and IoT use data to predict diseases and their stages. The data fusion approach is applied to structured and unstructured data and becomes structured data. After data fusion, the Preprocessing layer mitigates noise, missing values and resizes images. The proposed model imports data from the cloud for the prediction of diseases. If diseases do not detect, then it’s called negative. Otherwise, it is called positive. After predicting conditions, the proposed model imports data from the cloud to predict disease stages, and the proposed model will recommend a doctor or Hospital.

# Project Evaluation

In this portion, all experimental procedures, tests, and results discussed. It described the dataset details and division of training and testing instants for the proposed model. Next, the achieved accuracy and performance of the segmentation of proposed algorithms to the breast cancer prediction system.

In this proposed model fusion-based model used that produces the results by using both types of the dataset simultaneously with the help of machine learning approaches. The Fusion-based model deals with multiple datasets simultaneously. The First dataset will execute with deep extreme machine learning, and the second dataset will run with a Convolutional neural network. Finally, decision have taken based on fusion of both generated results. It increased the accuracy rate and reduce the chances of error compared with previous methods that have already been done of the intelligent breast cancer identification system.

Already many feature-based and image-based datasets are used separately by different researcher but unfortunately, these two different datasets follow the various models of machine learning to generate results independently.

## Problem Introduction

Breast cancer is a disease seen mainly in women and is a significant cause of death among women. In 2018, the total number of deaths due to breast cancer in women was seen to be 627,000 out of 2.1 million cases that were diagnosed. Invasive Ductal Carcinoma (IDC) in diagnosing breast cancer, since its subsequent digitalization is more feasible due to advancements in slide scanning technology and reduced storage load cost in recent years. The digitalized approaches in deep learning have aided a lot in diagnosing and controlling breast cancer, with the power to pre-identify the disease via deep learning methods. The CBIS (Curated Breast Imaging Subset) has provided a set of breast cancer images to analyze a machine or deep learning over it.

## Dataset Information

The dataset that I am given is composed of both image and tabular data. I have performed an EDA (Exploratory Data Analysis) on all data and devised a neural network model. The dataset contains over 10,000 scanned images of breast cancer, each image belonging to 2 sets of labels, named as malignant or benign. I have made a model such that given an image, the model classifies the image in one of the two cancerous tumours (malignant or benign). A benign tumour is less dangerous than a malignant tumour, and it can be controlled by taking safety measures. In other cases, the malignant tumour is a symbol of danger. It has a more excellent value of being affected the breast and caused cancer.

Summarizing all things, I have a dataset of almost 6GB in size, having the following characteristics:

* Scanned over 10,0000 breast cancer images
* Each image belonging to 2 labels, malignant or benign
* A tabular set of data is also given, which contains detailed information about all these sets of images

## Data Splits

For the sake of model fitting, I have made a split of 3 sets: train, validation and test:

* For training, I have included 70% of the data
* For validation the 20% of data is being kept, and
* The remaining 10% is for testing purposes.

Machine Learning, or simply ML, is a field of study that aims to make machines learn through data without being programmed explicitly and make decisions on unseen data intelligently. It is understood as a subset of Artificial Intelligence (AI), which aims to make machines behave intelligently like humans. The area of ML is divided into three parts, as given next:

* **Supervised Learning**

Type of machine learning works on labelled data and makes a function that maps the input to the given output.

* **Unsupervised Learning**

Type of machine learning that works on unlabeled data to draw valuable patterns from it and generate decisions.

* **Reinforcement Learning**

Type of machine learning that aims to train an agent in an interactive environment to achieve its goal.

Deep Learning is another class of machine learning that aims to solve tasks by using algorithms inspired by the working of the human brain. Deep Learning comprises deep neural networks that work like the functionality of biological neurons in our brains. As in machine learning, deep learning also contains many algorithms, referred to as deep neural networks, used for specific tasks; some of them are listed:

* **Convolutional Neural Network (CNN)**

Used for problems concerned with image-related tasks, like image classification, etc.

* **Recurrent Neural Network (RNN)**

Used for language-related tasks like language modelling

* **Deep Brief Networks (DBNs), and so on**
* **Multi-Layered Perceptron (MLP)**

Since my situation is concerned with neural network tasks, I will be using a multi-layered perceptron (MLP) to model our problem.

## Implementation Techniques

For this problem, I have used Python Programming Language as a tool. Python provides good libraries for machine and deep learning that will be used for our dataset, which is listed below:

* Scikit-learn (for machine learning)
* Keras (for deep learning)
* Pandas (for data preprocessing)
* NumPy (for array computing)

Each of these libraries has many built-in functions and methods that can be used for computing with images, tensors and arrays.

## Algorithms Used

I have used MLP (Multi-Layered Perceptron), a multi-layered neural network, to model our problem. This network can be accessed in the Keras and Scikit-learn library of python. The MLP contains multiple layers of neurons having sigmoid, tanh or ReLU (Rectified Linear Unit) as activation functions.

## Model Fitting & Evaluation

For making a neural network model, I have defined its evaluation and compilation metrics to calculate its results. This process involves some steps, as listed:

* Instantiate the MLP Model with default parameters, or apply them manually
* Define the optimizer function (Adam, SGD, etc.). For our case, I have used Adam Optimizer
* Define loss function (In our case, it is Crossentropy Loss or Log loss)
* Compile the model (by defining the loss function, optimizer)
* Set the number of iterations
* Fit the model to the data

## Model Results

After defining the model and fitting the neural network model to our training data, I got the following results. Following is an image showing the accuracy of the training and testing dataset:

Figure 4.1 shown the accuracy status of training and testing of the dataset. Basically dataset is divided into two parts, the first is training, and the second is testing. So the training accuracy is 73.2 %, and the testing accuracy is 72.4% by using the Convolutional Neural Network. It is a type of multi-level neural network proficient in identifying visual patterns through learning mechanisms. CNN specifies that the network implies a mathematical operation called convolution. Convolutional Neural networks are established, which utilize convolution in one of the multiple layers of the network rather than the widely known multiplication matrix. CNN uses fewer parameters and connections than the conventional feed-forward neural networks, which help the training get easier. Feature extraction and detection in CNN are not spatial dependents, and higher-level features are acquired as the input travels to the deeper layers.

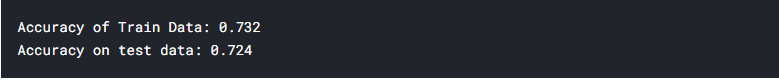


Figure 4.1: Accuracy status of Training and Testing

Since I have dealt with a classification problem, I must evaluate it using the confusion matrix. The picture below shows the confusion matrix of our model:

Figure 4.2 shows the dataset's confusion matrix, which classify the problem and evaluates it using proposed machine learning based approaches. Convolutional layers convolve the input and pass its result to the next layer. The majority of images are static. So feature learned in one section can resemble a pattern learned in a different section. In the case of a larger image, a small segment of a vast image is passes through all of the points in the extended image (Input). A filter is a small portion of an image that gives over a larger image (Kernel). After that, the filters are configured using the backpropagation technique.

The next layer after the convolution layer is non-linearity. The non-linearity layer can be used to change the output generated. This layer is used to saturate the output or reduce the output produced. Sigmoid and Tanh have previously been utilized as non-linearity but now Rectified Linear Unit (ReLU) functions are used commonly. ReLU has simple Function and Gradient definitions.

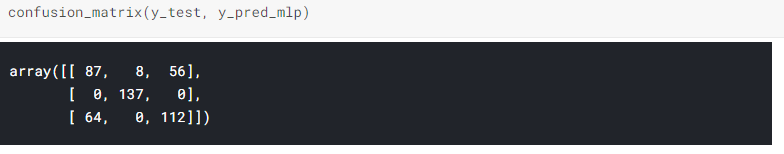


Figure 4.2: Confusion Matrix Screenshot

The performance of the classification model can also be accessed via a classification report. The classification report of my model is as given next:

Figure 4.3 shows the performance classification of the proposed model. This indicates the levels by adjusting the weight of the hidden layer and applying the multiple functins of the proposed model. Overall, 20 iterations have been done for the evaluation of the results of training and testing.

The down sampling of an image. The primary purpose of the pooling is to minimize the complexity of the input for the further corresponding layers. It takes the output of the small regions from the previous layer as input and generates a single output. Max Pooling is the most commonly used technique in this layer. It distributes the image into multiple rectangles, most commonly a 2 \* 2 region, and outputs the maximum pixel value of that region. The Pooling Layer decreases the number of parameters to be calculated.

A fully Connected Layer, like the conventional feed-forward nervous connection, integrates each neuron in one folding to every nerve cell in the succeeding. The first folding of the Fully Connected layer connects every node in a pool folding. A completely networked folding utilizes the most parameters and demands a significant number of complex coaching calculations. For the final prediction of the input image, the Fully Connected Layer is accountable.

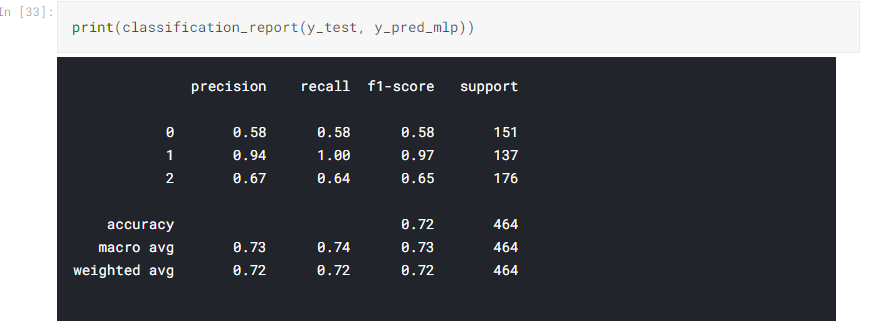


Figure 4.3: Classification Report

Let’s visualize the confusion matrix. The diagram of the confusion matrix as obtained in the evaluation of our model is as given below:

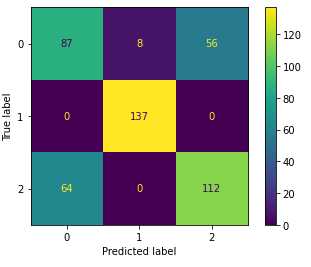


Figure 4.4: Visualization of Confusion Matrix

## Model Evaluation Graph

I have also calculated the graph for accuracy per iteration (epoch) on training and validation data. The chart is obtained as a result of complete model training for 20 iterations and is shown below:

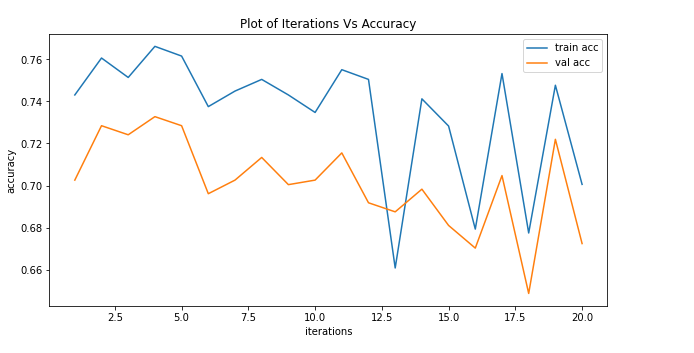


Figure 4.5: Epoch Graph for Training and Testing the Dataset

# Conclusion

Breast cancer is one of the significant types of cancer and a substantial cause of death rate among women. The only way to decrease it is to diagnose it at early stages. The preliminary determination of this research to design the automated system assists medical practitioners in diagnosing breast cancer disease by using machine learning techniques. The proposed method will use to analyze the stage of breast cancer quickly. The methodology in the present study showed the highest accuracy compared with previously reported studies on breast cancer diagnosis. This system will extensively change the conventional method, making the system more efficient, convenient, and personalized.

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