

# **An Intensive Analysis of Deep Learning Impacts on Breast Cancer Diagnosis and Practices**

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## **ABSTRACT**

Medical imaging allows for the visualization and mathematical modeling of biological processes that are critical for the screening mammography. Since it is limited by meritocratic abilities of high descriptive capability in visual assessment and traditional machine learning approaches, deep learning has been widely used in medical imaging research in recent years. Deep learning, as a broader model, demands less computational technology and enables for more accurate data volumes in forecasting. We present a study that uses deep learning to investigate aspects of breast cancer detection and diagnosis. Second, we present a mammography-specific deep learning model. Finally, we include an overview and input on recent work on deep learning systems for breast cancer detection and diagnosis, as well as some potential open issues.

**Keywords:** Breast Cancer, Deep learning, Machine learning, Medical imaging, Supervised Learning.

## **1. INTRODUCTION**

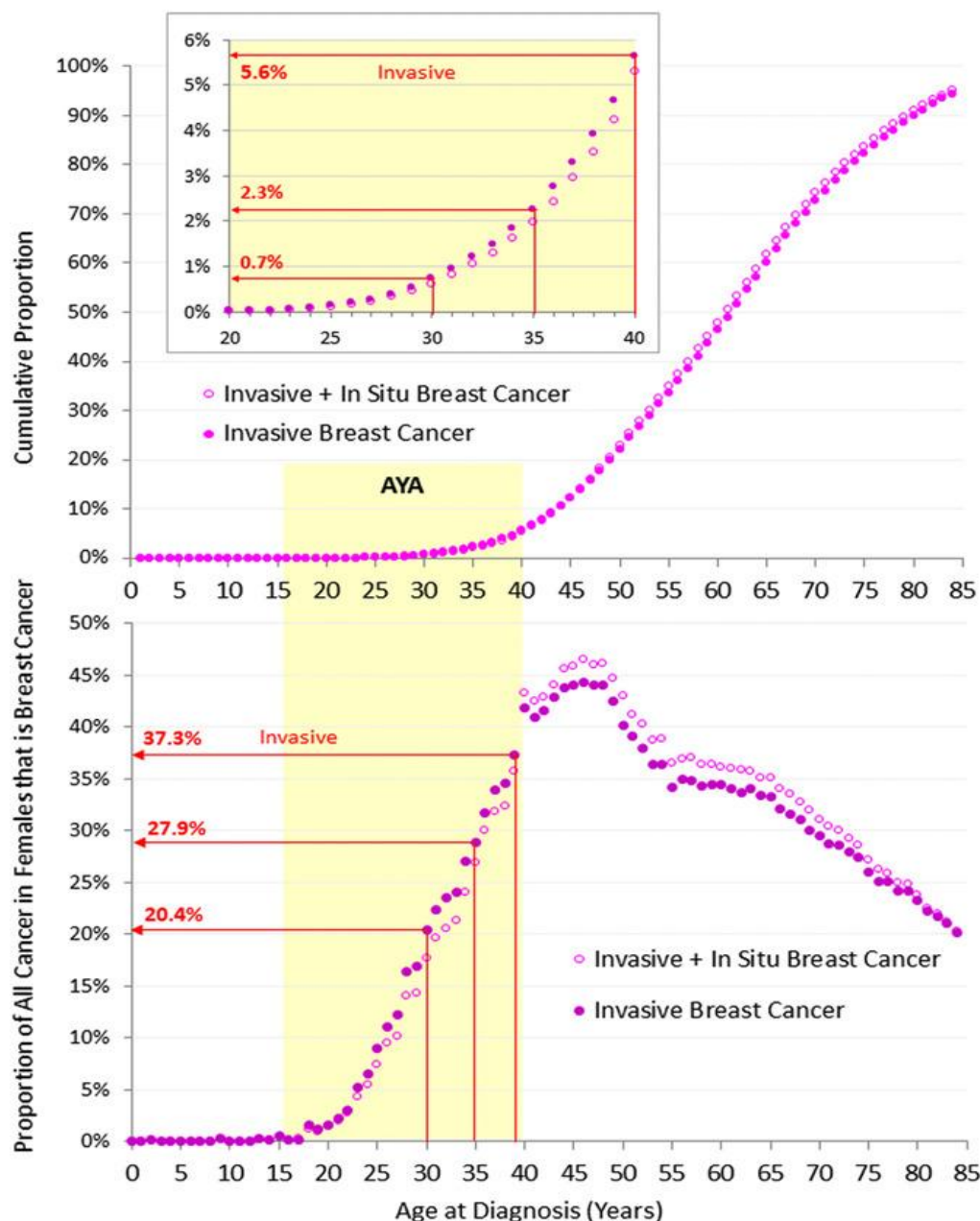
Deep learning is a form of education that is in close vicinity to a significant increase in computer power, advancement in model designs, and a substantial increase in data collection from cellular and other devices. Machine learning is classified into three categories: supervised learning, unsupervised learning, and enhanced learning. A classifier can use a training dataset that includes inputs and labels (outputs). Some popular supervised learning algorithms include linear and logistic regression, SVM, naive bayes, multilayer perceptron, genetic algorithms, and random forest. These methods are commonly used in classification and regression analyses. Unsupervised learning, on the other hand, does not use pre-existing output/labels and instead seeks out associations dependent on the representation of inputs. The most popular unrestricted type is clustering (e.g., K-means). Neural

networks can be supervised, unmonitored, or semi-controlled, demonstrating their adaptability in comparison to other recent unregulated approaches. Reinforcement learning can be described as a rewarding mechanism for maximizing rewards for the computer program in order to find the correct answer [1].

Deep learning is made up of multiple layers of neural networks that mimic neurons in the human brain. Similar to linear regression, each neuron has a weight value that is adjusted during the training algorithm by the stochastic gradient descent to mitigate the global loss function. By applying nonlinear behavior with activation function to the various levels of each neuron, more abstract mathematical structures were extracted from the input data to map to the output. As a result, a well-trained set can forecast new unlabeled data. Data mining is a branch of machine learning that encompasses a wide range of viewpoints, such as basic statistical generalizations, costs, and although providing more versatility, it can be constructed on complex layers with multiple neurons across each layer to provide powerful forecasting capabilities [2]. Deep learning is being used in notable biomedical studies to encode the pathogenic potential of gene changes, illustrate state-of-the-art performance in the function of genomic variant calling, and boost protein folding prediction. Deep learning is more flexible and streamlined than other strategies for isolated or ongoing procedures, needs less feature engineering knowledge than machine learning in general, and outperforms many cutting-edge techniques. Establishing deep learning algorithms for cancer diagnostics is a challenging technique. Before they can classify relevant data, these instruments must analyze clinically labeled examples from tens of thousands of patients [3].

In breast cancer pathology, achieving an appropriate dataset size is virtually impossible. Typically, researchers only have access to hundreds or thousands of pathology slides that have been annotated with the correct diagnosis. To solve this problem, the team invented a two-step method of priming the algorithm to identify unique patterns in cancerous tissue before teaching it the correct diagnosis. The first phase incorporates the idea of tissue fingerprints, or distinguishing design concepts in cancer tissue, which an optimization will use to distinguish between samples because no two patients are alike. Deep learning algorithms detect functional distinctions on pathology slides with greater precision and accuracy than the human eye, and recognize these variations without the need for human supervision [4]. The digital pathology images are categorized then used a deep learning algorithm to reassemble them based on their molecular fingerprints. This demonstrated the model's ability to group identical and distinctive pathology slides without the need for paired

diagnoses, enabling the team to train the algorithm on large, annotated datasets, a method known as self-supervised learning. Researchers implemented the second stage of the deep learning tool after training the algorithm to identify the structure of breast cancer tissue that distinguishes patients: learning which of the defined patterns is related to a particular diagnosis [5].



**Figure 1.** Adolescents and young adults are affected by breast cancer forms.

With this thorough introduction to deep learning's contribution to breast cancer diagnosis, this study makes a significant contribution to analyzing various aspects of the general process of

applying breast cancer diagnosis in Sections 2 and 3. Section 4 discusses deep learning applications for cancer diagnosis, followed by a conclusion in Section 5.

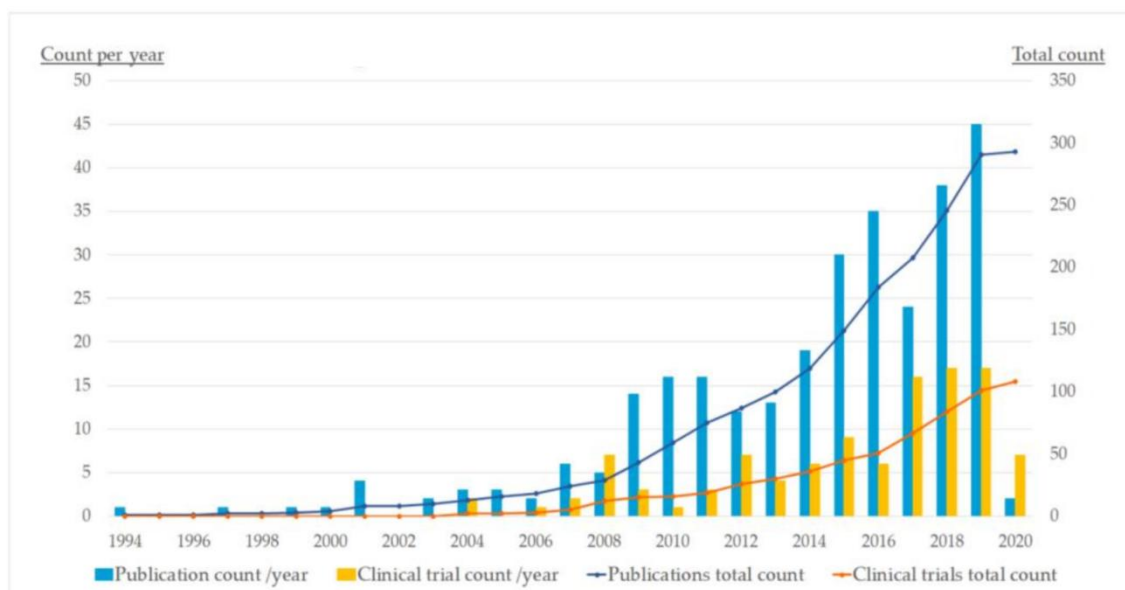
## **2. ASPECTS OF DEEP LEARNING IMPACTS IN MEDICAL IMAGING**

### **2.1 Roadmap of deep learning in medical imaging**

One of the first applications of deep learning in medical image processing was classification. The detection of diagnosed images falls under the category of diagnostic images, where every diagnosed examination is a sample and the data size is smaller than that of machine vision. Artifacts or lesions are usually divided into two or more groups. Right classification for both of these tasks requires both local and global awareness of the presence and location of lesions. The segmentation task requires the detection of anatomical artifacts such as organs and lesions as a pre-processing step. To locate the object in an image, several systems have been proposed to transform 3D space as a combination of 2D orthogonal planes using 3D image parsing. There was a long study trend involving the use of computer-aided techniques in the identification of lesions in a medical image, with the aim of improving detection precision or reducing detection time for humans. Surprisingly, the first such technique, which used a CNN with four layers to diagnose nodules in X-ray images, was developed in 1995 [6]. Organ and other structural elements in medical images are segmented using a systematic study of form, scale, and volume. Usually, the segmentation task is defined as identifying a group of pixels that define contours or artifacts.

The role of target recognition as well as organ and substructure segmentation is included in the implementation of deep learning algorithms when segmenting lesions. Since the majority of pixels in an image are from a non-infected class, injury segmentation correlates object identification with class imbalance. The traditional task of image analysis, also known as spatial alignment, is to calculate the transformation of coordinates from one image to another. This is generally achieved in an iterative method that assumes a specific form of transformation and optimizes a pre-trained metric. Although lesions detection and object segmentation are the most popular applications of deep learning algorithms, researchers have discovered that deep networks can aid in achieving the best possible registration results [7]. There are also other deep learning applications of medical imaging. Content-based image recovery is a method of searching through broad databases for information that offers similar case history data retrieval and identifies rare disorders. Image extraction and enhancement is another project that uses deep learning to enhance image quality, normalize images,

complete data, and identify patterns. Integrating image data with reports is another work that appears to have a large-scale application in the real world.



**Figure 2.** Number of publications in cancer clinical trials

This has aided in the application of results from two related research areas: (1) improving image classification precision; (2) generating text reports from images [8]. Figure 2 depicts the number of publications so far in cancer clinical trials.

## 2.2 Protease biology in cancer

Proteolysis is important in both normal and pathological metabolism, and these antioxidants are involved in cancer growth and spread. We are now able to comprehend the role of proteases, from unidentified proteolytic enzymes to modern perception of the different roles of the protease in a diverse microenvironment when changing and reporting. Proteases will be used in cancer diagnosis and treatment for the next decade as a result of this deeper view. Protease activity may be tested for diagnosis as a biomarker of cancer with several benefits ranging from early diagnosis to clinical response surveillance. While cancer protease dysfunction has been recognized since the 1940s, a deeper view of cancer improvement facilities via protease activity has emerged. The numerous and varied functions of proteases in the cancer microenvironment have been extensively investigated, including the roles of metalloproteinases, cathepsins, and tissue kallikreins[9].

### **2.2.1 Cell Growth**

Signals and cell proliferation that are affected by protease action regulate cell growth. The bioactivity of TGF- has been shown to affect a number of matrix metalloproteinases (MMPs), namely MMP2, MMP9, and MMP14, which may help cancer growth. Other proteases that can result in cancer cells, such as ADAM10 (disintegrating and metalloproteinase) and ADAM17, can regulate the bioactivity and abundance of EGFR. As cell surface ligand controllers, sheddases are necessary for a variety of signaling procedures. Development factors control kallikrein peptidases (KLKs), which are similar to KLK2. Cathepsin B (Ctsb) is involved in the catabolism of lysosomes, which are essential for life. Cathepsins play a variety of cancer-related roles; for example, Ctsb knock-out mice have significantly slowed cancer growth in many cancers, but the toxin has no impact in a melanoma model. Besides that, in a mouse model of breast cancer, removing Ctsb increased Ctsz activity, which can result in phenotypes. The stochastic removal of cathepsin revealed similar compensatory mechanisms. This complex relationship between multiple proteases and their substances in cancer development serves as a cautionary lesson against treating a single protease or a family of proteolytic enzymes [10].

## **2.2 Survival**

Survival is commonly used as a policy metric to determine the burden of cancer and to evaluate cancer outcomes across populations. However, it is well recognized that survival is more vulnerable to prejudices than community mortality (such as lead time and length biases). Longer survival can mean future deaths, but it can also indicate early identification or over diagnosed with no improvements in death (detection of cancer situations that progress so slowly that the person dies of other causes). Incidence of cancer is the number of individuals in a particular who have been treated for cancer, while cancer survival is the percentage of people who are still alive for a certain period of time. The cancer risk is the likelihood of contracting cancer or dying from it within or over a set period of time. To avoid cell death, cancer cells use protease-mediated regulation to inhibit pathways. Modulation and degradation of the Fas ligand by MMP7 and ADAM10, for example, may prevent caspase-mediated apoptosis. Similarly, CTSS is unregulated in the presence of ionizing radiation, resulting in increased cell survival and lower clinical performance [11].

## **2.3 Angiogenesis**

Angiogenesis is the process of the current vasculature expanding. It happens in both good health and poor health throughout one's life, from childhood to old age. An angiogenesis-formed blood capillary is several hundred microns thicker than any metabolically active tissue in the body. Epithelial cells are needed in all tissues for the diffusion of nutrients and metabolites. Changes in metabolism result in differential angiogenesis and, as a result, proportional capillary changes. The angiogenic switch is needed for cancers to progress from mystic lesions of 1-2 mm in diameter, allowing for effective transfer of metabolites and growth metabolites. MMP9 is a potent angiogenesis initiator since it regulates VEGF solubility. CTSS can produce proangiogenic pieces, similar to MMP9, but other specific sections have antiangiogenic properties. The deterioration of tissue insulin receptor substrate inhibitors by cathepsins, and therefore the dissolution of changing the volume by MMPs, has an effect on the relationship (cysteine protease inhibitors). Similarly, KLKs regulate angiogenesis by destroying the extracellular matrix and stimulating MMPs, with pro- or antiangiogenic effects [12].

## **2.4 Invasion**

Invasion necessitates cancer cells rapidly expanding and invading neighboring tissues. Transformed cells proliferate, and the tumor grows in size over time, eventually breaking through the tissue barrier and expanding into neighboring tissue. The factor that enables cancer cells to travel from their primary site in their disease is a mutation of genes that control protein production, which normally binds cells to their tissues. Local invasion is a normal part of the primary growth phase of secondary tumors and metastases. Owing to abnormal enzyme synthesis ability to degrade the connections between cells and tissues, cancer cells are able to escape the predominant tumor due to decreased cell synthesis of a variety of substances related to surrounding cells. The degradation of the ECM by different proteases, such as MMPs, cathepsins, kallikreins, and other serine proteases, arbitrates the development of cancer cells to various sites. uPA, in combination with its receptor and plasminogen, plays a key role in extracellular matrix degradation by inducing MMPs. KLK1 activates MMP2 and MMP9, while KLK2, KLK4, and KLK15 activate uPA, thus regulating invasion[13].

## **2.5 Inflammation**

Inflammation is a defense mechanism of your body's white blood cells that protects you from infection by outside invaders such as bacteria and viruses. When inflammation occurs, chemicals from white blood cells in the body combine with blood or tissues to defend the body from invading compounds. The amount of blood flowing to the area of injury or infection is increased. It is possible to trigger redness and warmth. Fluid spills into the tissues and swells as a result of each of these chemical compounds. This defense has the potential to irritate nerves and cause pain. Signaling to parenchymal and immune cells on a daily basis can be protumorigenic. TNF- $\alpha$  works by causing ADAM17, a proinflammatory cytokine, to become enabled. MMP8 frequency, in particular, promotes inflammation by producing PGP (N-acetyl Pro-Gly-Pro) and inducing neutrophils to infection sites. Cathepsins and legumes were known to be involved in tissue inflammation when cancer cells were created[14].

## **2.3 Types of cancer**

### **2.3.1 Mammography**

Breast cancer arises as cells in the breast begin to form in an unbalanced manner. These cells usually aid in the prevention of cancer, which may appear as a lump on an x-ray or be felt. If the cells may grow into (invade) or spread (metastasize) surrounding tissues, the cancer is malignant. A method to reliably assess if a person is experiencing breast cancer or not by analyzing biopsy photographs. Breast cancer is the most common cancer among women, accounting for approximately one-third of all newly diagnosed cancers, according to previous studies. Since people's lives are on the line, the algorithm had to be extremely precise. Breast cancer is also a high-mortality disease, responsible for 17% of all cancer-related deaths. Right diagnosis and treatment of breast cancer in its early stages is critical for lowering the death rate. Mammography has traditionally been the most effective tool for general population screening. However, identifying and diagnosing a breast lesion based solely on mammography findings is difficult and highly dependent on the radiologist's abilities, resulting in a high number of false positives and additional tests[15].

### **2.3.2 Lung carcinoma**

Lung carcinoma, the most common cancer in both men and women, is a major health problem that affects people all over the world. According to some estimates, nearly 221,200 new lung cancer cases were diagnosed in 2015, accounting for about 13% of all cancer diagnoses. Lung

cancer accounts for around a fifth of all cancer-related deaths. Lung nodules must be closely examined and controlled for a number of purposes, as they may be in an early stage of growth. Early diagnosis increases the 5-year survival rate of pulmonary cancer patients by around 50%. Because of its ability to produce 3D images of lung nodules, the CT is the most effective measure of diagnosis for lung nodules, due to better resolution and tumor pathology. In the clinic, a computer-processed CT image was commonly used to help in the diagnosis of lung nodules. A defensive system (often referred to as CAdE) and a control strategy make up the computer controlled lung cancer diagnostic process (CAD) (often referred as CADx). Candidates discovered during the previous step are classified as nodules or non-nodules using the CAdE method (i.e., normal anatomic structures). The CADx method is used to differentiate between benign and malignant nodules. Given the high risk of malignancy, CADx can differentiate between benign and malignant pulmonary nodules based on size, form, and growth rate. Diagnostic, speed, and elastomer materials' efficacy can thus be calculated in the output of a specific CADx unit. In recent years, neural networks, rebranded as deep learning, have begun to take on conventional AI in every critical task: speech recognition, image detection, and quick, easy-to-read statements. Deep learning not only boosts computer accuracy and CT image performance recognition and classification, but it also accelerates the vital mission[16].

### **2.3.3 Intracranial Tumor**

Intracranial Tumor is initiated by the formation of abnormal cell groups within or near the brain. Abnormal cells cure the brain and have an effect on the patient's health. The study's main emphasis is on brain imaging exams, care, and management for surgeons, radiographers, and medical specialists using adopted treatment tests. Since brain cancer, also known as brain cancer, is lethal and causes a large number of deaths in developed countries, brain image analysis is deemed significant. The importance of brain image processing cannot be overstated. For the management and care of a brain tumor, a number of imaging techniques and methods have been used. The basic stage in the processing of images is segmentation, which is used to remove the contaminated area of the brain tissue from MRIs. For separating, categorizing, and forecasting cancer in the future, Stacked Denoising and Boltzmann Convolutional Selective Autoencoders have more in-depth learning strategies. When it comes to segmenting, identifying, and predicting pictures, CNNs outperform all other deep learning strategies[17].

### **2.3.4 Melanoma**

Melanoma is a cancer that affects many people. Every year, approximately 5.4 million new cases of skin cancer are discovered in the United States alone. The figures on a global scale are equally alarming. According to new research, the number of new melanoma cases diagnosed each year increased by 53% between 2008 and 2018. The death rate from this disease is expected to rise over the next decade. The survival rate is less than 14% when diagnosed in the final stages. When skin cancer is detected in its early stages, however, the survival rate is about 97 percent. This involves detecting skin cancer at an early stage. An unclear eye examination with abnormal lesions, dermoscopy, and biopsy are usually performed by a qualified dermatologist. This takes time and will lead to the patient's progression to the next level. Furthermore, a good diagnosis is subjective and based on the clinician's ability. The best dermatologist was found to be less than 80% effective in correctly diagnosing skin cancer. Aside from these impediments, there aren't enough trained dermatologists in public health care around the world[18].

### **2.3.5 Adenocarcinoma**

Male adenocarcinoma is the most common cause of cancer death. It was the third leading cause of cancer death in men in 2017. Despite the fact that prostate cancer is the most common form of cancer, survival rates are high when detected early on due to the disease's slow progression. As a consequence, accurate assessment and early diagnosis are the keys to improving patient survival. A variation of prostate-specific antigen testing, automated rectal inspection, trans-rectal ultrasound, and magnetic resonance imaging are used to diagnose clinically relevant prostate cancer (PCa) (MRI). PSA screening, on the other hand, leads to overdiagnosis, which in turn leads to ineluctably costly and painful needle biopsies, as well as overdiagnosis. In radiologic environments where the area under the receiver operating characteristic curve (ROC) differs from 0.69 to 0.81 for radiologists detecting PCa, multiparametric MRI, a highly diffusion-weighted imaging device, has increasingly become the standard of care for prostate cancer diagnoses. While radiologists have developed a standardized PI-RADS v24 framework for image interpreters, there are still issues with facts and circumstances when using the PI-RADS system[19].

## **3. STAGES AND METHOD IN MAMMOGRAM**

Among the most common and prominent applications in the deployment of deep learning algorithms for breast cancer detection is computer vision. It is the most prominent deep learning

framework for detecting cancer using images, despite the fact that it is also possible to identify structured data with common supervised problems [20][21]. There are three stages to the process:

### **3.1. Pre-Processing**

Distortion of raw images enhances image quality by removing unwanted picture detail, also known as image noise. The first stage of the detection phase is preprocessing. There will be some inconsistencies in the ranking if this question is not handled correctly. Because of the poor contrast between the skin and healthy skin, the lack of hair, skin contours and dark backgrounds, irregular borders, and skin artifacts, this preparation is essential. To eliminate noise from generalized linear, speckle, Poisson, and salt and pepper, a variety of filters are used, including mid-sized, medium, adaptive median, gauze, and adaptive Wiener. A pattern means that hair in it, like an injury, may result in misclassification. Pre-processing work such as camera calibration, vignetting removal effects, color correction, image smoothing, hair removal, standardization, and translation can all help to reduce or remove noise. Precision is improved by using the right combination of pre-processing functions. MRIs of cancer patients are first colored grey, then smoothed. The computed tomography used to diagnose breast cancer is normalized using X-ray instruments that are first transformed into grey images before going through the normalization process. These images are converted to binary images, and the unwanted parts are then deleted. Breast cancer preprocessing necessitates a strong past cancer delineation, elimination of the breast margin, and pectoral stimulation. Many sounds are used in mammograms to diagnose breast cancer, including a rectangular high mark, a low-intensity label, and tape items. Transrectal ultrasound (TRUS) images are acquired with inherent noise and low pictorial precision for prostate cancer diagnostics. Marking, orientation, and segmentation of mammograms are thus accomplished. The intrusion and artifact suppression preprocessing module has been upgraded.

- Tree-Structured nonlinear Filtering (TSF);
- Directional Wavelet Transformation (DWT); and
- Tree-structured Wavelet Transformation (TWT).

### **3.2. Image Segmentation**

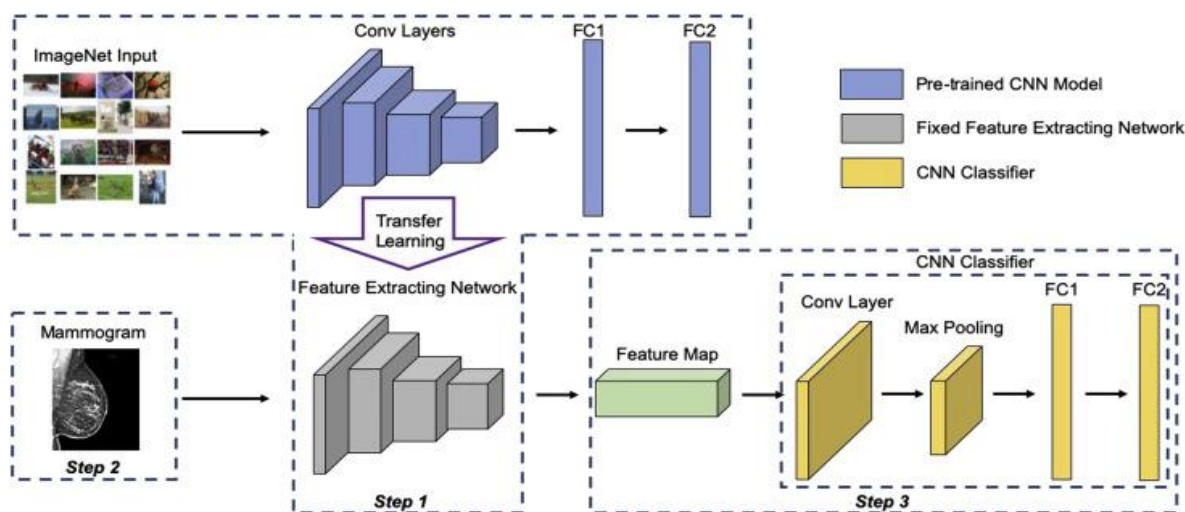
Segmentation is the distinction between the image in the input and the domains where the required data can be obtained for further study. The main aim of segmentation is to differentiate

between a region of interest and the image's context (ROI). ROI includes the image we want to use. The lesion part of breast cancer images must be isolated from the diseased area.

- Threshold based
- Region based
- Pixel based
- Model based

Cutoff point distribution, maximum likelihood, local and global thresholds, and vectorscope thresholds all benefit from the Otsu process. Watershed segmentation and planting area extension are two examples of area segmentation. The Fuzzy c-means clustering, artificial neural networks, and the Markov field approach are all methods in the pixel dependence segmentation class. Histogram thresholds, adaptive measures, mean velocity flow and recognition, convergence and creation of statistical areas, bootstrap processing, contour lines, edge detection, aggregation, probabilistic modeling, sparse encoding, hyper contextual, co-operation, and edge-detection are several other image segmentation strategies. These approaches were combined in hybrid versions to improve the method's accuracy by integrating two or more of them.

### 3.3. Post-Processing



**Figure 3.** Diagnosing cancer using deep learning

Following the pre-processing and image segmentation processes, post-processing is used to acquire characteristics. The most popular post-processing methods are area dumping, area melting, border extension, and flattening. Principal components analysis, transforming wavelet collection, grey level matrix, and Fourier power spectrum are some of the extraction techniques used. The

approach is focused on deep learning, which is the classification of images using deep neural networks. These deep neural networks are of a specific kind that allows for relatively efficient image processing. CNNs, or convolutional neural networks, are what they're called. Neural networks may produce what are known as activation maps. This is nothing more than a compilation of heat maps describing the areas on which the model has been based in order to make a specific forecast. In the preceding image, the areas on which the model was centered to determine that this picture is not carcinogenic are shown in grey. The areas that were used to determine if it is carcinogenic are highlighted in yellow. As a result, the expert will be able to see the parts that the model believes are critical in the forecast [22].

#### **4. APPLICATION AND RESEARCH DIRECTIONS IN FIGHTING CANCER**

##### **4.1 Gene expression**

It's difficult to detect carcinoses using gene expression data because of its high dimensionality and uncertainty. Scientists were able to use a deep learning approach to identify breast cancer cells in order to derive important features from gene expression data. DeepGene is a deep learning classifier based on somatic mutation that tackles issues with existing cancer classification study. It's a comprehensive classification system focused on somatic point mutations. The DeepGene model performed above three widely agreed grades in terms of computational somatic point mutation and special forms of cancer, according to the report.

##### **4.2 Cancer classification**

The network is the same as all of the experts who were questioned about skin cancer classification. The Google CNN Platform has shown how long-term skin cancers can be diagnosed at rates that are acceptable for clinicians, enabling them to join diagnostics further away from the clinic and provide service applications that have increased in popularity as mobile access has spread across the world.

##### **4.3 Tumor segmentation**

Deep learning in MR images of brain tumor segments produced more reliable results as compared to doctors manually distinguishing tumors who are susceptible to movement and vision errors. Deep information in ultrasound shear wave echocardiography can accurately differentiate between benign and malignant breast tumors, resulting in elastogram accuracy of over 95 percent for over 250 patients.

#### **4.4 Histological Examination**

For histological examination, a thin slice (panel) of tissues is examined with a light (optical) or electron microscope. Histopathology is a microscopic biopsy test used in clinical medicine and basic science to diagnose and classify diseases. In order to diagnose cancer, histopathologists examine the regularities of cell type and tissue distribution visually, determine the cancer area of the tissue, and assess its malignancy in histology images. The workload and complexity of histological (microscopic tissue analysis for the evaluation of disease manifestations) in cancer diagnosis will increase as the focus of medical testing shifts to the protection and accuracy of personalized medicine. The use of deep learning enhances the efficacy of histopathic slide analysis, reducing pathologists' workload and growing diagnostic objectivity.

#### **4.5 Tracking tumor**

Intensive analysis may be used to assess the size of treatment tumors as well as the existence of fresh and probably undetected metastases. The CT and MRI patient will be more reliably scanned the deeper the learning algorithm is scanned. Deep learning instruments that complement pathologists' workflow are also difficult to build, according to Google Research. Images were used to train a deep learning algorithm for detecting breast cancer (including Google Net) that has spread to the lymph nodes in the surrounding area. The method had an accuracy of 89 percent among pathologists, compared to 73 percent among non-pathologists.

#### **4.6 Prognosis detection**

The prognosis shows the size or development of the cancer stage and, as a result, the chances of survival. Cancer staging systems are valuable, but they have limitations when it comes to predicting a patient's prognosis. Deep learning is being used to build a prognosis prediction model for patients with gastric cancer (i.e. gastrectomy). When compared to other prediction models, deep learning has shown to have superior predictive survival abilities.

### **5. CONCLUSION**

Cancer is the leading cause of death worldwide. Both researchers and doctors are grappling with the nuances of cancer treatment. According to the American Cancer Society, there were 96,480 skin cancer deaths in 2019, 142,670 lung cancer deaths, 42,260 breast cancer deaths, 31,620 prostate cancer deaths, and 17,760 brain cancer deaths in 2019. For many people, early cancer detection is

the most important priority in order to save their lives. Visual scans and manual procedures are widely used to diagnose these types of cancer. Medical image manuals take a long time to study and are prone to mistakes. This paper is the first to explain aspects of deep cancer treatment, including measures for breast cancer diagnosis with doctor-style stages. The final section of this manuscript includes applications and research recommendations that explain how deep learning models have been effective in treating different types of cancer.

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