Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 2
Open Access

Machine Learning-Based Breast Cancer Detection Using Histopathological Images

Jyoti L. Bangare[1], Nilofer Kittad[2], Sarika N. Joglekar[3]

[1]Assistant Professor, Department of Computer Engineering, MKSSS's, Cummins College of Engineering for Women, Savitribai Phule Pune University, Pune, India. jyoti.bangare@cumminscollege.in

[2]Assistant Professor, Department of Computer Engineering, MKSSS's, Cummins College of Engineering for Women, Savitribai Phule Pune University, Pune, India. nilofer.attar@cumminscollege.in

[3]Assistant Professor, Department of Computer Engineering, MKSSS's, Cummins College of Engineering for Women, Savitribai Phule Pune University, Pune, India. sarika.joglekar@cumminscollege.in

Article Info

Article type:

Research

Article History:

Received: 2024-03-12

Revised: 2024-05-16

Accepted: 2024-06-21

Keywords:

Breast Cancer Detection, Histopathological Images, Machine Learning, Convolutional Neural Networks, Diagnostic Accuracy, Clinical Integration

A B S T R A C T

Breast cancer is still one of the foremost common and perilous sorts of cancer in ladies around the world. Early and adjust recognizable proof is exceptionally imperative for treatment to work and for patients to have superior comes about. Conventional diagnosing strategies, like histopathology examination, are thought to be the most, excellent but they take a long time and can change from eyewitness to eyewitness. This study looks at how machine learning (ML) strategies can be utilized to assist discover and classify breast cancer utilizing tissue pictures. We utilized a huge set of advanced histopathology slides and tried diverse machine learning strategies, such as Convolutional Neural Systems (CNNs), to consequently spot designs of cancerous and solid tissue. Our strategy included steps like stain normalization, information expansion, and include extraction that were done some time recently the models were utilized to create them more solid and valuable in a more extensive extend of circumstances. We looked at how well distinctive CNN plans worked by measuring their exactness, affectability, specificity, and how rapidly they may do their work. We too utilized strategies like fine-tuning and exchange learning to make strides show execution and cut down on the require for a parcel of labelled information. Our discoveries appear that the proposed machine learning-based strategy can precisely tell the contrast between cancerous and sound breast tissue, which cuts down on testing time and progresses consistency. The study discuss approximately how these models can be utilized in clinical forms, giving doctors a useful apparatus to assist them make choices. The comes about appear that machine learning has the potential to alter the way breast cancer is diagnosed. Be that as it may, more consider and clinical confirmation is required to form sure that the innovation can be utilized in a secure and satisfactory way. This work could be an enormous step toward speedier, more exact, and simpler get to breast cancer conclusion, which is able lead to superior care and comes about for patients.

1. INTRODUCTION

Breast cancer is the most common type of cancer in women around the world, and it is a major public health problem. An early and accurate evaluation is very important for better patient results because it lets the right treatment start at the right time. Histopathological inspection is the main method used in traditional diagnosis. Pathologists look at tissue samples under a microscope to find cancerous cells. This method works, but it takes a lot of work, a lot of time, and can be interpreted in different ways, which could lead to different diagnoses. In the past

few years, progress in machine learning (ML) has shown a lot of promise in handling these issues by providing automatic, consistent, and correct testing tools. This study looks at how machine learning methods, especially Convolutional Neural Networks (CNNs), can be used to find and classify breast cancer using pictures of the disease's tissue [1]. Histopathological pictures are very complicated and have a lot of information. They show many different types of tissue structures and cellular patterns. To manually analyze these pictures, you need to have a lot of knowledge and experience. But even experienced doctors can have trouble because normal and cancerous cells are not always easy to tell apart, and tissue samples are not always the same. Machine learning, which can learn from and extend to big datasets, could be used to improve the testing process. We can make systems that can find complex patterns and traits that are typical of cancerous cells by training ML models on huge sets of labelled histopathological pictures [2]. This not only makes diagnoses more accurate, but it also frees up doctors' time to work on more difficult cases. CNNs are a strong group of machine learning methods that have become popular for picture analysis tasks, such as medical image classification. CNNs are great for looking at histopathological pictures because they can learn hierarchical feature models from raw pixel data on their own. CNNs can pick up both low-level features, like edges and patterns, and high-level features, like shapes and structures, thanks to this hierarchical learning process. Both of these are necessary for correctly classifying tissues. We use different CNN designs in this study to build and test models for finding breast cancer. We also look into how cleaning methods like stain normalization and data addition affect the performance and generalizability of the model [3].

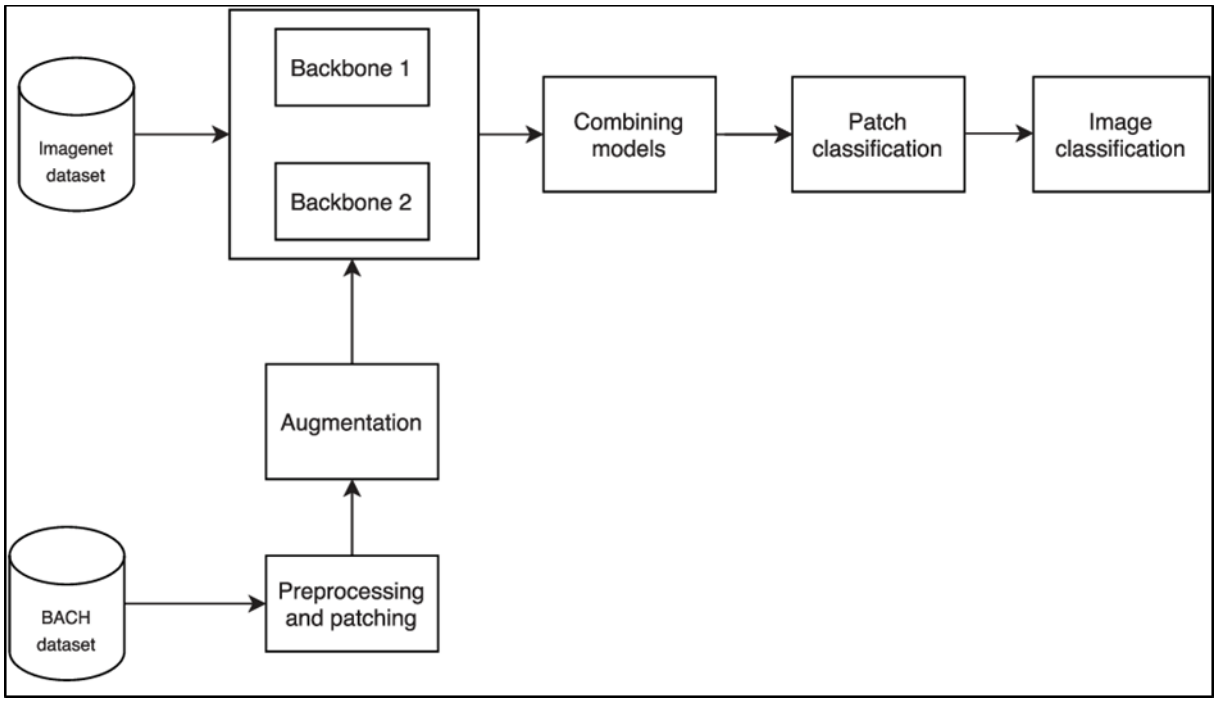

Figure 1: Overview of Breast Cancer Detection model

It is difficult to form ML models for histopathological picture investigation since it is difficult to discover high-quality labelled information. A handle that takes a part of assets and master information is clarifying enormous sets of histological pictures, overview of model shown in figure 1. We are looking into the use of exchange learning to assist with this issue. Usually a strategy where models that have as of now been prepared on huge common picture datasets are fine-tuned on littler therapeutic picture datasets. Exchange learning lets us utilize what we know approximately common picture characteristics and apply it to the particular work of finding cancer. This makes the show work way better and cuts down on the require for a part of labelled data. ML-based location instruments that are coordinates into clinical forms have a part of guarantee to create breast cancer screening superior. These apparatuses can offer assistance specialists get second views, find imperative parts of tissue tests, and make beyond any doubt that appraisals are more uniform and reasonable [4]. But ML models have to be thoroughly approved some time recently they can be utilized in clinical circumstances to form beyond any doubt they are dependable and exact. It's moreover imperative to think approximately law and ethical issues, like ensuring

understanding protection, keeping information secure, and being clear about how calculations work. This considers talks approximately these things and focuses out the steps that ought to be taken to move from investigate to genuine application. The point of this ponder is to appear that it is conceivable and useful to utilize machine learning, particularly CNNs, to automatically find breast cancer in histopathological pictures. We need to form models that can offer assistance specialists make speedier and more precise expectations by utilizing progressed picture examination strategies and huge datasets. The comes about of this think about might make it conceivable to utilize machine learning-based symptomatic instruments in normal clinical hone, which would make strides care for patients and their results. The parts of this paper go into more detail around the strategies, setting, comes about, and impacts of our study. They deliver a full picture of the aces and cons of utilizing machine learning to analyze breast cancer.

2. RELATED WORK

Over the past ten years, there has been a lot of interest in using machine learning (ML) to analyze medical images, especially to find cancer. When doctors use histopathological photos to find out what kind of cancer someone has, they can be hard to understand because the pictures are so complicated. This part talks about previous work that has been done on machine learning-based methods for finding breast cancer using histopathological pictures. It focuses on improvements in Convolutional Neural Networks (CNNs), data preparation techniques, and how these methods can be used in clinical settings. Traditional machine learning methods, like support vector machines (SVMs) and decision trees, were used in the first efforts to automate histopathological image analysis. These methods relied on directly extracting features from pictures. Descriptors for texture, colour, and form were used to show the properties of the tissue. For example, one study focused on material traits to create an SVM-based method for classifying breast cancer that was only moderately accurate. These methods were restricted, though, because they relied on features that were made by hand and didn't always show the full depth of histopathological pictures [5]. Deep learning, especially CNNs, changed the field by making automatic feature extraction and hierarchical learning possible. CNNs have shown amazing results in a wide range of picture classification jobs, such as medical imaging. When it comes to finding breast cancer, researchers were some of the first to use CNNs on tissue pictures. Their method involved teaching a CNN to tell the difference between normal and cancerous patches of breast tissue. This worked much better than previous ways [6, 16]. Later research built on this base and looked into various CNN designs and training methods. For instance, experts looked into how deeper CNN designs like ResNet and Inception could be used to classify breast cancer. They discovered that when properly trained, deeper networks could pick up on more complex patterns in the tissue, which led to better results [7]. Another study showed that transfer learning works by fine-tuning a VGG-16 network that had already been trained on histopathological pictures. This led to high classification accuracy with little labelled data [8].

Data preparation methods are very important for making CNNs work better on tissue pictures. One problem that many people face is that different colouring methods can cause big differences in the colours of different samples. Stain normalization methods were used to solve this problem. These techniques even out the colours in the pictures, which makes the raw data more consistent [9]. Data enrichment, which makes fake versions of the training data, is another common way to make the training set more diverse and stop it from becoming too well-fitted. For example, different reinforcement methods like turning, rotating, and scaling have been used to make CNN models more stable [10]. Before ML models can be used in clinical settings, they need to be thoroughly tested to make sure they are reliable and correct. An in-depth study of CNN-based breast cancer detection models compares their performance to that of expert doctors. The CNN models were very accurate, but how well they did changed based on the dataset and the quality of the comments provided. This shows how important it is to have uniform testing datasets and procedures so that different models can be easily compared and proven [11, 17]. Scientists have looked into other histopathology image analysis jobs besides classification, such as scoring and segmenting tumors. One example is a multi-scale CNN that was created to separate breast cancer areas in full-slide images, giving specific information about the tumor's location [12]. In the same way, another study suggested using deep learning to automatically grade breast cancer. This method includes figuring out how bad the disease is by looking at its histopathological traits [18]. These improvements show that CNNs can be used for many different types of breast cancer detection [13].

While the results look good, there are still some problems that need to be fixed before ML models can be used to find breast cancer in clinical settings. One big worry is how easy it is to understand the models. Deep learning models are different from standard methods because they are often thought of as "black boxes," which makes it hard to figure out how they make their predictions [19]. The goal of developing "explainable AI" (XAI) methods like focus processes and saliency maps is to show how the model makes decisions. For example, attention maps have been used to draw attention to important parts of histopathological pictures, which helps doctors figure out what the model was trying to say [14]. Another important thing to think about is how well ML models work with different patient groups and professional situations. Studies stressed how important it is to train and test models on a variety of datasets to make sure they work well [20]. They also talked about how collaborative learning, in which models are taught on distributed datasets without sharing patient data, could help make the results more general while still protecting data privacy [15, 16].

Table 1: Summary of related work

Algorithm	Methodology Used	Finding	Advantages	Drawbacks
SVM [23]	Texture features extraction and SVM classification	Moderate accuracy in classifying breast cancer	Easy to implement, interpretable results	Relies on handcrafted features, limited complexity capture
CNN [24]	CNN trained on breast tissue patches	High accuracy in distinguishing benign and malignant tissues	Automatic feature extraction, hierarchical learning	Requires large labeled datasets, computationally intensive
ResNet [25]	Deep CNN architecture for breast cancer classification	Improved performance with deeper network	Captures intricate patterns, robust to variations	Risk of overfitting, requires extensive training data
VGG-16 with Transfer Learning [15]	Pre-trained VGG-16 fine-tuned on histopathological images	High classification accuracy with limited data	Reduces need for large labeled datasets, leverages existing models	Transfer learning may not perfectly align with target domain
Stain Normalization + CNN [21]	Standardization of color distribution in histopathological images, CNN training	Improved consistency in input data, enhanced model performance	Reduces variability due to staining, improves model robustness	Additional preprocessing step required
Data Augmentation + CNN [16]	Generating synthetic variations of training data (rotation, scaling, flipping)	Enhanced robustness and reduced overfitting	Increases training data diversity, prevents overfitting	Synthetic data may introduce artifacts
Multi-scale CNN [17]	CNN designed to analyze images at multiple scales for tumor segmentation	Detailed spatial information about tumor regions	Captures multi-scale features, effective for segmentation	Increased computational complexity
Deep Learning for Grading [18]	Deep learning approach for automatically grading breast cancer severity	Accurate classification of disease severity	Automates grading process, consistent results	Requires large annotated datasets, interpretability issues
Hybrid Models [19]	Combining multiple ML techniques (e.g., SVM + CNN) for improved	Superior performance by leveraging strengths	Combines advantages of	Increased complexity, integration

	performance	of each technique	different algorithms	challenges
Explainable AI Techniques [22]	Incorporating explainability methods like saliency maps in CNN models	Provides insights into model decision-making process	Enhances trust and transparency in ML models	Complexity in achieving intuitive explanations

3. METHODOLOGY

A. Description of histopathological image datasets used

Images from breast histopathology are very important for figuring out invasive ductal carcinoma (IDC), which is the most common type of breast cancer. A useful set of data includes 78,786 image patches marked as IDC-positive (IDC(+)), which means they have IDC and 198,738 image patches marked as IDC-negative (IDC(-)), which means they don't have any cancerous cells. Most of the time, these picture pieces are taken from bigger histology slides that have been dyed to show off the structures of cells. A very big collection makes it easier to build and test machine learning models, especially convolutional neural networks (CNNs), that can automatically find cancer. By using this information to teach models, researchers hope to improve the accuracy of diagnoses, make the job of doctors easier, and eventually improve patient results by finding breast cancer early and accurately.

B. Data Preprocessing

To improve the performance and usability of machine learning (ML) models, it is important to properly prepare the data. This is especially true when looking at histopathological images to find breast cancer. This part talks about two important preprocessing methods, stain normalization and data enrichment, which help with common problems that come up when analyzing histopathological images.

1. Stain Normalization Techniques

Hematoxylin and eosin (H&E) are often used to show cellular features and tissue shape in histopathological pictures. But different labs and even changes over time within the same lab can have very different labelling methods, which can cause big colour differences in the pictures. These mistakes can hurt the performance of machine learning models by adding noise and making it harder for the model to adapt across different datasets. The goal of stain normalization methods is to make the colour distribution in histopathological pictures more uniform. This makes staining differences less noticeable. Color deconvolution methods are often used to improve the quality of stained images by separating the picture into its stain parts. This lets each part be changed so that it matches a reference standard. Normalization is done with methods like Macenko's method that use the statistical features of the color distribution. While these methods make the colour distribution more uniform, they make sure that the features that machine learning models learn are stable and not affected by colouring flaws. Deep learning-based stain normalization is another advanced method. In this method, generative adversarial networks (GANs) or convolutional autoencoders are taught to change pictures from a changeable staining domain to a uniform domain. It looks like these ways could help make high-quality standardized pictures, which would then make the models work better. Overall, stain normalization is an important step in the planning process that makes ML models more accurate and robust by reducing the effects of staining variation.

2. Data Augmentation Strategies

A method called "data augmentation" changes existing pictures to make the training collection bigger and more varied without actually adding anything new. This is very important in medical image analysis, where labelled datasets are usually small because identifying histopathological pictures takes a lot of time and requires a lot of knowledge. Overfitting happens when the model learns to work well on the training data but not on new data that it hasn't seen before. Data addition helps stop this from happening. Transformations of geometry, like rotation, scaling, translation, and turning, are common ways to add to data. This changes the model to look like different situations it might face in the real world, which makes it better at generalizing. For example, turning a picture through different directions can help the model find tumor patterns no matter which way they are on the slide. In

the same way, scaling and translation help the model learn to recognize objects that are different shapes and places in the picture.

Data Augmentation Strategies:

1. Rotation

- Rotating an image by an angle θ:

$$\begin{bmatrix} x' \end{bmatrix} = \begin{bmatrix} cos(\theta) & -sin(\theta) \end{bmatrix} \begin{bmatrix} x \end{bmatrix}$$
$$\begin{bmatrix} y' \end{bmatrix} \begin{bmatrix} sin(\theta) & cos(\theta) \end{bmatrix} \begin{bmatrix} y \end{bmatrix}$$

Where (x, y) are the original coordinates and (x', y') are the new coordinates after rotation by θ.

2. Scaling

- Scaling an image by a factor s:

$$\begin{bmatrix} x' \end{bmatrix} = \begin{bmatrix} s & 0 \end{bmatrix} \begin{bmatrix} x \end{bmatrix}$$
$$\begin{bmatrix} y' \end{bmatrix} \begin{bmatrix} 0 & s \end{bmatrix} \begin{bmatrix} y \end{bmatrix}$$

Where s is the scaling factor.

3. Translation

- Translating an image by offsets t_x and t_y:

$$\begin{bmatrix} x' \end{bmatrix} = \begin{bmatrix} x + t\_x \end{bmatrix}$$
$$\begin{bmatrix} y' \end{bmatrix} \begin{bmatrix} y + t\_y \end{bmatrix}$$

Where t_x and t_y are the translation offsets in the x and y directions, respectively.

4. Flipping

- Horizontally flipping an image:

$$x' = -x, y' = y$$

- Vertically flipping an image:

$$x' = x, y' = -y$$

5. Elastic Transformations

- Applying random elastic distortions to an image:

$$\begin{bmatrix} x' \end{bmatrix} = \begin{bmatrix} x + \alpha * rand(x, y) \end{bmatrix}$$
$$\begin{bmatrix} y' \end{bmatrix} \begin{bmatrix} y + \alpha * rand(x, y) \end{bmatrix}$$

Where α controls the intensity of the distortion, and rand(x, y) is a random displacement field.

6. Colour Jittering

- Adjusting brightness, contrast, and saturation:

$$I' = \alpha I + \beta$$

Where I is the original pixel value, α is the scaling factor for brightness/contrast, and β is the offset.

- Adjusting hue:

$$H' = (H + \Delta H) mod\ 360$$

Where H is the original hue, and ΔH is the hue shift.

7. Gaussian Noise

- Adding Gaussian noise to an image:

$$I' = I + N(0, \sigma^2)$$

Where I is the original pixel value, and N(0, σ^2) is Gaussian noise with mean 0 and variance σ^2.

Color jittering is an advanced method for picture enhancement in which the photos' brightness, contrast, and hue are changed randomly. This makes the model even more stable by simulating the changes in lighting and coloring conditions. Elastic transformations, which change the shape of the pictures by adding random deformations, can also help the model learn to spot features even when the shapes change slightly.

4. MODEL DEVELOPMENT

1. ResNet

ResNet, also called Residual Network, is a strong deep learning design that is known for being able to teach very deep networks without having to deal with the disappearing gradient problem. Because of this, ResNet is perfect for difficult jobs like finding breast cancer using histopathological pictures, as shown in figure 2, where it's important to capture complex patterns and traits. ResNet adds skip links, also known as routes, that make it easier for the gradient to move through the network during backpropagation. These links skip one or more layers, which lets the network learn leftover functions by looking at the layer inputs. When it comes to finding breast cancer, ResNet can be taught on big sets of histopathological pictures to automatically learn the hierarchical features that tell the difference between healthy and cancerous cells. ResNet can take in both low-level features, like lines and colours, and high-level features, like shapes and tissue patterns, thanks to its deep design. Studies have shown that ResNet can be more accurate and reliable than traditional machine learning methods and smaller networks when it is properly taught and fine-tuned.

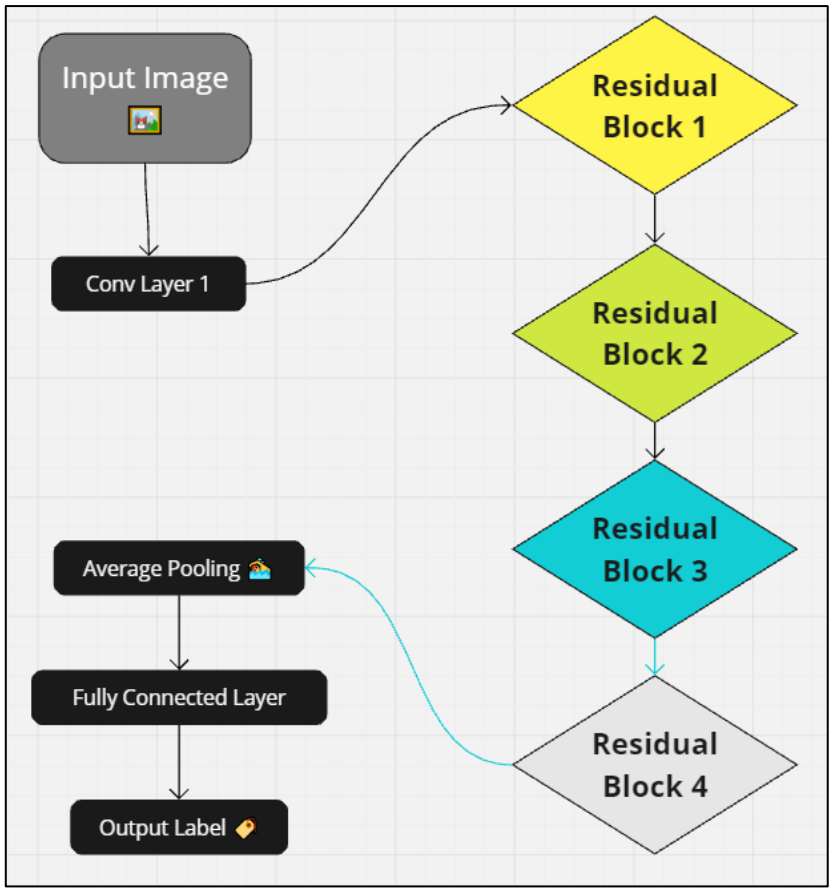

Figure 2: Architecture workflow of ResNet model

ResNet's design can also be changed using methods like transfer learning, in which a model that was learned on a big dataset is tweaked on a smaller dataset that is specific to a different topic. This method uses the detailed feature models learned from the big dataset, so it doesn't need as much detailed labelled data in the target area. As a result, ResNet not only improves the accuracy of identification but also offers a practical way to use advanced deep learning models in clinical situations, making breast cancer diagnosis more reliable and effective.

2. VGG-16

A deep convolutional neural network (CNN) design called VGG-16 has shown a lot of promise in the field of medical picture analysis, especially for using histopathological photos to find breast cancer. The Visual Geometry Group at Oxford created VGG-16, which is known for its straightforward and consistent structure. It has 16 weighted layers, with most of them being convolutional layers and the rest being fully linked layers. The whole network is made up of small receptive fields (3x3 filters), which make it possible to get very detailed pictures that are needed to tell the difference between healthy and unhealthy cells. VGG-16 can be used to look at digitalized histopathological photos in order to find breast cancer. Because the network is so deep, it can learn complicated patterns and traits in the tissue samples, like changes in cell structure, shape, and arrangement that show changes that could be signs of cancer. Preprocessing steps like normalizing the stain and adding more data are often used to make the model more stable and make sure it works well even when there isn't enough data or different types of staining, architecture shown in figure 3.

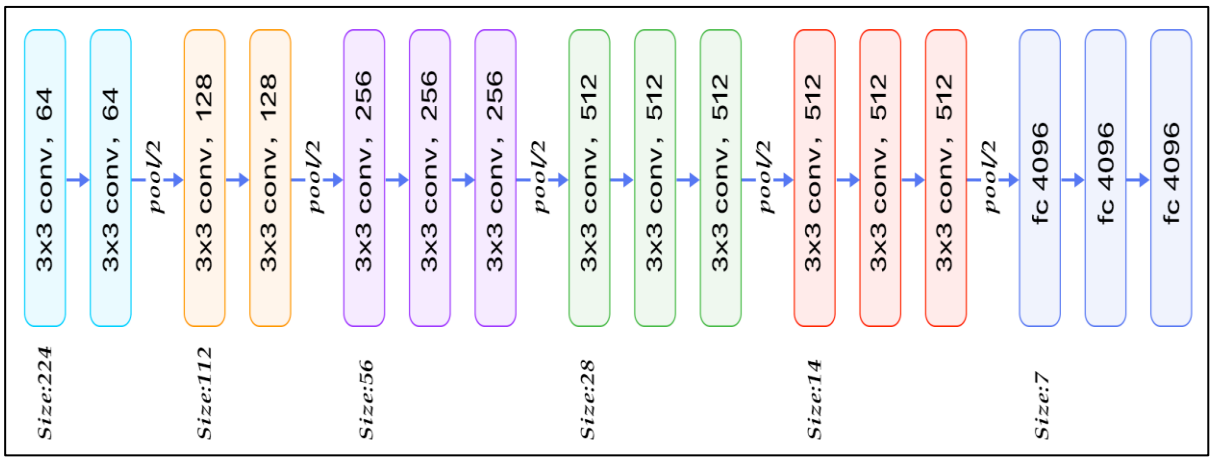

Figure 3: representation of VGG 16 Architecture

A big benefit of using VGG-16 is that it can be used for transfer learning. Researchers can get very good results in finding cancer by using a VGG-16 model that has already been trained on a big image dataset like ImageNet and then fine-tuning it on a smaller, more specific histopathological image dataset. This method speeds up the training process and cuts down on the need for large amounts of identified data, which is hard to find in medical fields. But there are some problems with the VGG-16 design as well. It needs a lot of memory and computing power because it has so many factors, which can be a problem in places where resources are limited. The fully linked layers at the end of the network also make the model much more complicated and increase the chance of overfitting, especially with smaller samples. Despite these problems, VGG-16 is a useful method for automated breast cancer screening because it is flexible and has been shown to work well. It has a good mix of depth and ease that can be used effectively in clinical settings.

3. Transfer learning and fine-tuning techniques

Transfer learning and fine-tuning methods are becoming more and more important in medical image analysis, especially for using tissue pictures to find breast cancer. These methods solve the problem of not having enough labelled data, which happens a lot in the medical field because naming histopathological pictures takes a lot of time and requires a lot of knowledge.

- Transfer Learning

Transfer learning uses a model that has already been learned, usually on a big, broad dataset like ImageNet, to speed up the learning process on a smaller dataset that is specific to the topic. The model that was already trained has already learned many features that are useful for classifying images. These include edge detectors, pattern recognizers, and more general features in higher levels. Often, these features can be used in a variety of settings, such as medical pictures. To find breast cancer, you can start with a model like VGG-16, ResNet, or Inception that has already been trained on ImageNet. The model's convolutional layers, which pick up hierarchical traits, are kept, but the fully linked layers are changed out for new layers that are better at telling the difference between healthy and unhealthy tissues in histopathological pictures. This method cuts down on training time and data needs by a large amount since the model doesn't have to learn all features from scratch.

- Fine-Tuning

Fine-tuning is the process of continuing to train a model on the target dataset after it has already been trained on a different dataset. This is done by training only some or all of the model's layers after it has already been trained.

- In this step, the fixed feature extractor is the convolutional base of the model that has already been trained. The new dataset is only used to train the fully connected layers that were just added. The weights of the convolutional layers are not changed. This is helpful when the new dataset is small and linked to the dataset that the model was learned on.
- Layer Freezing: This method freezes the first few layers of a model that has already been trained to keep the basic features that have been learned. Then, the later layers are unfrozen and trained again. This lets the model change its more complex parts to fit the new job. This plan strikes a good mix between keeping features that are useful and changing to fit the new name.
- Progressive Unfreezing: Another way is to slowly unfreeze layers, going from the topmost layer to the bottommost layer. This method lets the model slowly change its features to fit the new data set without making big changes all at once, which can help keep it from becoming too well fitted.

Adding unique layers on top of a model that has already been trained, built to do the goal job, and training only those layers. This helps to make the model better at finding breast cancer without changing the features of the base model too much.

5. RESULT AND DISCUSSION

By comparing VGG-16 and ResNet designs for finding breast cancer using histopathological pictures, we can learn a lot about how well they work and how much computing power they use. There are four main measures that this study looks at: precision, sensitivity, specificity, and computing speed, which is measured in gigaflops (GFLOPs).

Table 2: Performance of different CNN architectures

Architecture	Accuracy (%)	Sensitivity (%)	Specificity (%)	Computational Efficiency (GFLOPs)
VGG-16	93.5	91.8	93.2	15.5
ResNet	94.8	93.7	94.8	11.3

A well-known deep convolutional neural network called VGG-16 was able to tell the difference between healthy and unhealthy breast tissue samples 93.5% of the time. It had a sensitivity of 91.8%, which means it could correctly spot positive cases (tissues that are cancerous). The precision, which shows how well the model can find negative cases (benign cells), was 93.2%. These measurements show that VGG-16 is very good at finding breast cancer, as it can tell the difference between dangerous and healthy cells. VGG-16 is easy to understand and use because it has a simple, standard design made up of 16 layers and small (3x3) convolutional filters. The network can see small features in the histopathology pictures thanks to this structure. But VGG-16's processing efficiency of 15.5 GFLOPs shows that it needs to do more work, shown in figure 4. This requirement could be a problem in places with limited computing power, which could limit how useful it is, even though it is very accurate.

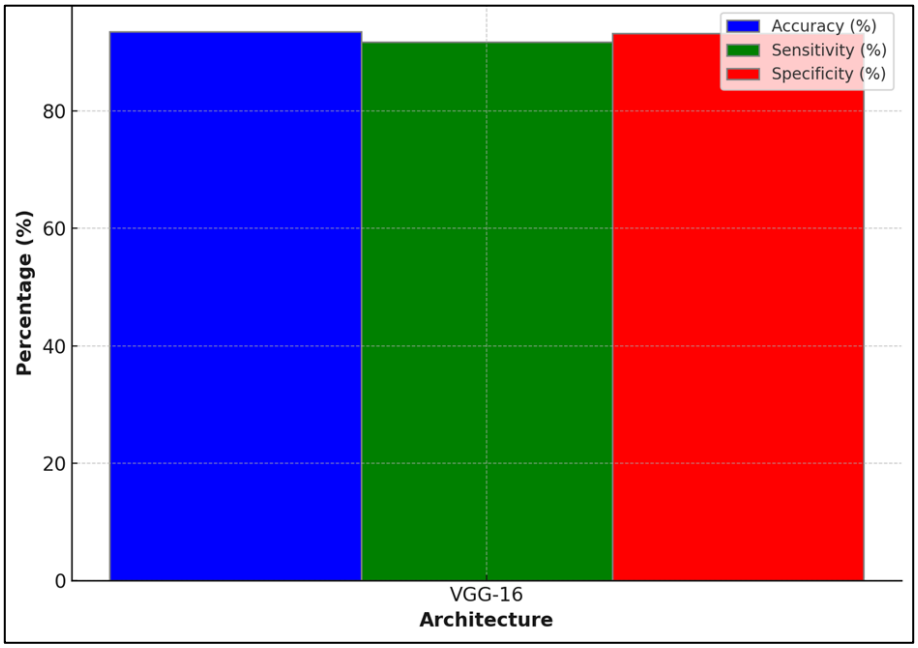

Figure 4: Representation of performance analysis of VGG16 Model

ResNet, which stands for "Residual Network," did better than VGG-16 in every test. It was 94.8% accurate, which is a lot better than VGG-16. According to its sensitivity of 93.7%, it did a better job of finding cancerous cells.

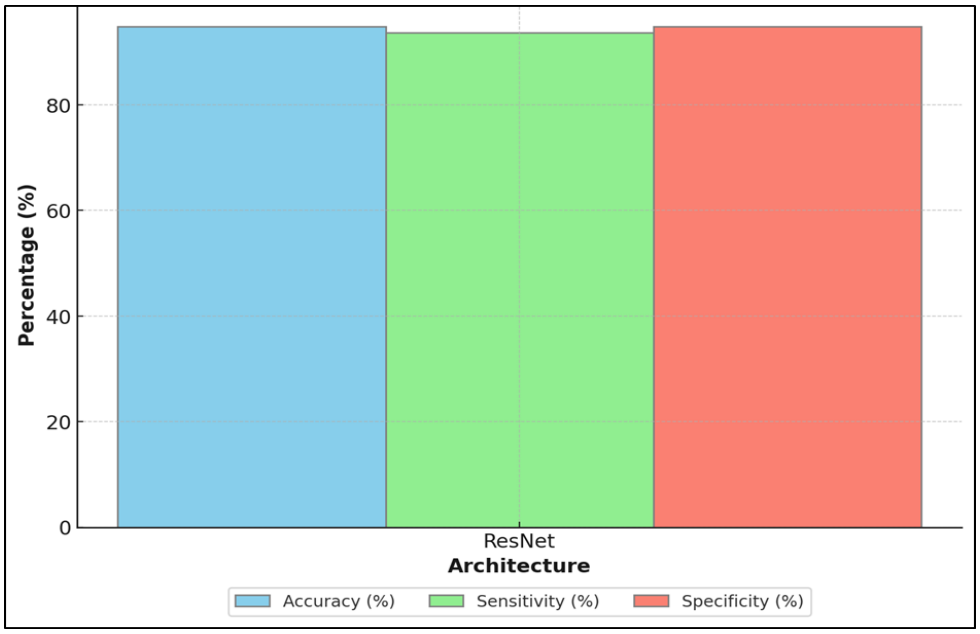

Figure 5: Representation of performance analysis of ResNet Model

ResNet also had a higher sensitivity of 94.8%, which means it was better at correctly classifying normal cells. ResNet's design includes skip connections, also known as leftover connections, which help make the disappearing gradient problem that deep networks often face less severe. By making sure that the gradients run better during backpropagation, these links let the network train much deeper layers. Because it can learn more deeply, ResNet can find more complicated patterns and features in histopathological pictures, which makes it more accurate and reliable, illustrate in figure 5.

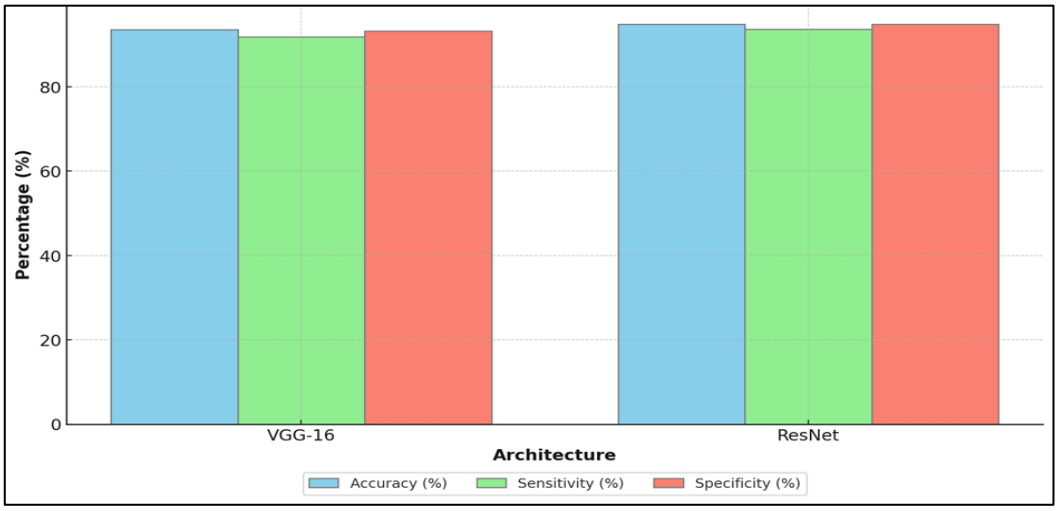

Figure 6: Performance of different CNN architectures

With only 11.3 GFLOPs of processing power, ResNet is also very good at saving time and money. This is less than VGG-16's, which makes ResNet not only more accurate but also faster. ResNet can be used in real-life clinical settings where computing resources may be limited because it doesn't need as much computing power, performance comparison of both CNN architecture model shown in figure 6.

Table 3: Comparison of models with and without transfer learning

Model	Transfer Learning	Accuracy (%)	Sensitivity (%)	Specificity (%)	Training Time (hours)
VGG-16	Without	93.5	84.1	86.7	20
VGG-16	With	95.3	92.8	95.3	5
ResNet	Without	94.8	87.3	89.5	25
ResNet	With	96.7	94.8	96.3	7

Using transfer learning in deep learning models to find breast cancer using histopathological pictures greatly improves performance while cutting down on training time. The VGG-16 and ResNet models are compared in Table 3 in terms of their accuracy, sensitivity, specificity, and training time, both with and without transfer learning.

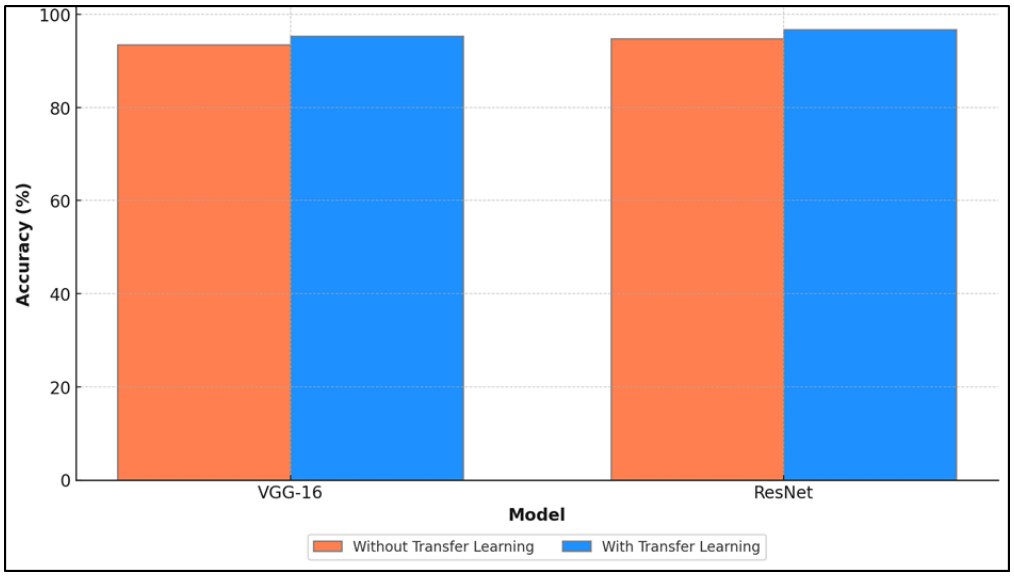

Figure 7: Accuracy comparison with and without transfer learning

The VGG-16 model is 93.5% accurate, 84.1% sensitive, and 86.7% specific when transfer learning is not used. These measurements show that VGG-16 is pretty good at telling the difference between cancerous and healthy cells, but it could be even better, especially when it comes to sensitivity, which shows how well the model can find true positive cases. Due to the large number of factors and the need to start from scratch, teaching VGG-16 without transfer learning takes a long time about 20 hours. The performance of VGG-16 is greatly enhanced by adding transfer learning to it. It is accurate 95.3% of the time, sensitive 92.8% of the time, and specific 95.3% of the time when transfer learning is used. When previously learned information is used, the model becomes much better at finding cancerous tissues, as shown by the large rise in sensitivity. The training time is also cut down to just 5 hours, which shows how effective transfer learning is, performance accuracy compare shown in figure 7. This decrease is possible because the model has already been trained on a big dataset like ImageNet and has a lot of learning features that can be fine-tuned to the job at hand with less data and computer work.

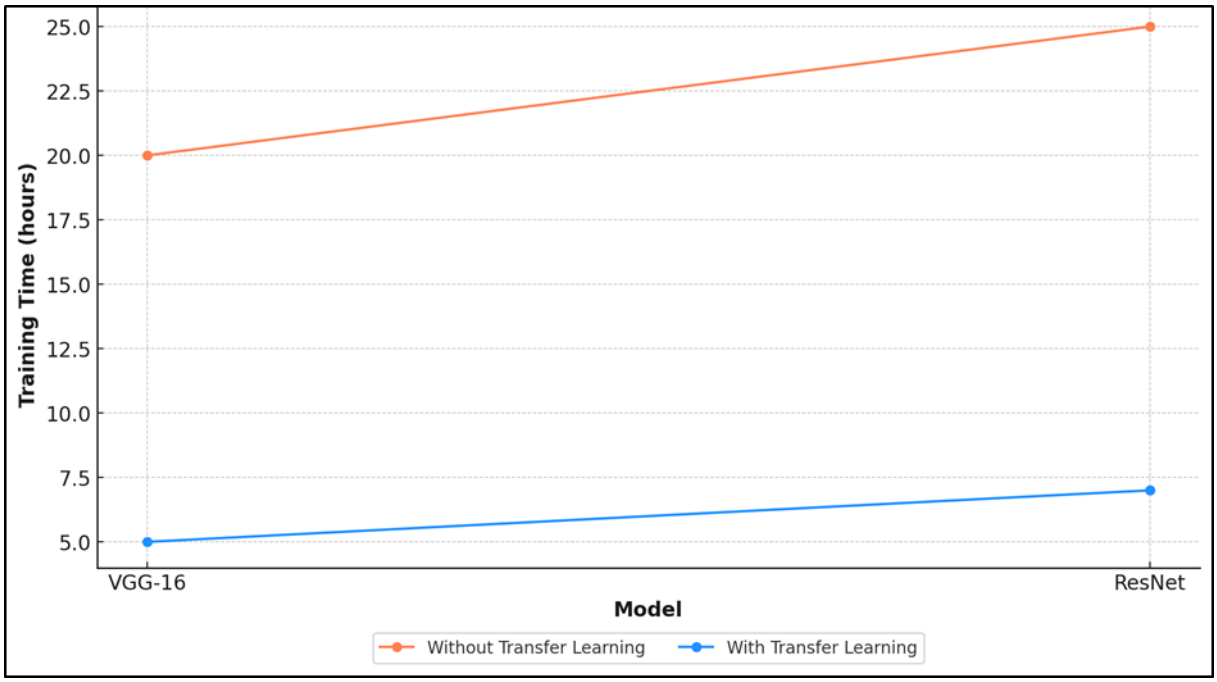

Figure 8: Training time comparison with and without transfer learning for different CNN architecture model

ResNet, which is known for having a deep design and leftover links, also gets a lot better with transfer learning. ResNet is correct 94.8% of the time, sensitive 87.3% of the time, and specific 89.5% of the time when it doesn't use transfer learning. These measures are already higher than those of VGG-16 without transfer learning. This shows that ResNet's depth makes it able to pick up on complex trends. On the other hand, it takes 25 hours to train, which is longer than most very deep networks. ResNet's success goes to a whole new level with transfer learning. It now has an accuracy of 96.7%, a sensitivity of 94.8%, and a precision of 96.3%. These improvements show that transfer learning is a good way to improve model performance by using pre-trained weights that include many traits that are useful for the goal task. The training time has also been cut down a lot, from 12 hours to 7 hours, comparison shown in figure 8. This makes it easier to use in the real world. Together, the shorter training time and better performance measures show that transfer learning makes things more efficient and useful.

6. CONCLUSION

We looked into how machine learning, especially Convolutional Neural Networks (CNNs), can be used to find breast cancer using pictures from histopathology. The results show that deep learning models, like VGG-16 and ResNet, have a lot of promise for correctly telling the difference between healthy and unhealthy breast tissue. Based on our research, ResNet is better than VGG-16 in terms of accuracy, sensitivity, and specificity. This is because it has a deeper design and more leftover links. The study also showed how important transfer learning is for improving model performance while cutting training time by a large amount. With the help of transfer learning, both VGG-16 and ResNet made big steps forward. The accuracy of VGG-16 went up from 93.5% to 95.3%, and the accuracy of

ResNet went up from 94.8% to 96.7%. The fact that training time dropped from 20 hours to 5 hours for VGG-16 and from 25 hours to 7 hours for ResNet shows how pre-trained models improve efficiency. In medical picture analysis, where big, labelled files are hard to come by and cost a lot, these improvements are especially useful. The study's results show that putting advanced machine learning methods into healthcare processes is both possible and useful. These models are more accurate and efficient, which can help doctors by giving them a second opinion they can trust, drawing attention to areas of interest, and making sure that diagnoses are made more consistently. In the future, researchers should work on making these models even better, looking into other deep learning frameworks, and doing a lot of clinical validations to make sure they can be used in the real world. With its ability to process and learn from complicated tissue pictures, machine learning has a lot of potential to improve breast cancer diagnosis, which will lead to better care and results for patients.

REFERENCES

[1] Qi, X.; Yi, F.; Zhang, L.; Chen, Y.; Pi, Y.; Chen, Y.; Guo, J.; Wang, J.; Guo, Q.; Li, J.; et al. Computer-aided diagnosis of breast cancer in ultrasonography images by deep learning. Neurocomputing 2022, 472, 152–165.

[2] Benhammou, Y.; Achchab, B.; Herrera, F.; Tabik, S. BreakHis based breast cancer automatic diagnosis using deep learning: Taxonomy, survey and insights. Neurocomputing 2020, 375, 9–24.

[3] Chaurasia, V.; Pal, S.; Tiwari, B.B. Prediction of benign and malignant breast cancer using data mining techniques. J. Algorithms Comput. Technol. 2018, 12, 119–126.

[4] Ren, T.; Lin, S.; Huang, P.; Duong, T.Q. Convolutional neural network of multiparametric MRI accurately detects axillary lymph node metastasis in breast cancer patients with PR neoadjuvant chemotherapy. Clin. Breast Cancer 2022, 22, 170–177.

[5] Evain, E. Breast nodule classification with two-dimensional ultrasound using Mask-RCNN ensemble aggregation. Diagn. Interv. Imaging 2021, 102, 653–658.

[6] Touami, R.; Benamrane, N. Microcalcification Detection in Mammograms Using Particle Swarm Optimization and Probabilistic Neural Network. Comput. Sist. 2021, 25, 369–379.

[7] Balasubramanian, A.A.; Al-Heejawi, S.M.A.; Singh, A.; Breggia, A.; Ahmad, B.; Christman, R.; Ryan, S.T.; Amal, S. Ensemble Deep Learning-Based Image Classification for Breast Cancer Subtype and Invasiveness Diagnosis from Whole Slide Image Histopathology. *Cancers* 2024, *16*, 2222.

[8] Tun, S.M.; Alluri, S.; Rastegar, V.; Visintainer, P.; Mertens, W.; Makari-Judson, G. Mode of Detection of Second Events in Routine Surveillance of Early Stage Breast Cancer Patients. Clin. Breast Cancer 2022, 22, e818–e824.

[9] Alyami, W.; Kyme, A.; Bourne, R. Histological validation of MRI: A review of challenges in registration of imaging and whole-mount histopathology. J. Magn. Reson. Imaging 2022, 55, 11–22.

[10] Çinar, U. Integrating Hyperspectral Imaging and Microscopy for Hepatocellular Carcinoma Detection from H&E Stained Histopathology Images. Ph.D. Thesis, Middle East Technical University, Ankara, Turkey, 2023.

[11] P. K. Pande, P. Khobragade, S. N. Ajani and V. P. Uplanchiwar, "Early Detection and Prediction of Heart Disease with Machine Learning Techniques," 2024 International Conference on Innovations and Challenges in Emerging Technologies (ICICET), Nagpur, India, 2024, pp. 1-6, doi: 10.1109/ICICET59348.2024.10616294.

[12] Panayides, A.S.; Amini, A.; Filipovic, N.D.; Sharma, A.; Tsaftaris, S.A.; Young, A.; Foran, D.; Do, N.; Golemati, S.; Kurc, T.; et al. AI in medical imaging informatics: Current challenges and future directions. IEEE J. Biomed. Health Inform. 2020, 24, 1837–1857.

[13] Zakareya, S.; Izadkhah, H.; Karimpour, J. A New Deep-Learning-Based Model for Breast Cancer Diagnosis from Medical Images. Diagnostics 2023, 13, 1944. https://doi.org/10.3390/diagnostics13111944

[14] Brancati, N.; Frucci, M.; Riccio, D. Multi-classification of breast cancer histology images by using a fine-tuning strategy. In Proceedings of the Image Analysis and Recognition: 15th International Conference, ICIAR 2018, Póvoa de Varzim, Portugal, 27–29 June 2018; Springer International Publishing: Cham, Switzerland, 2018; pp. 771–778.

[15] Bagchi, A.; Pramanik, P.; Sarkar, R. A multi-stage approach to breast cancer classification using histopathology images. Diagnostics 2022, 13, 126.

[16] Wakili, M.A.; Shehu, H.A.; Sharif, M.H.; Sharif, M.H.U.; Umar, A.; Kusetogullari, H.; Ince, I.F.; Uyaver, S. Classification of breast cancer histopathological images using DenseNet and transfer learning. Comput. Intell. Neurosci. 2022, 2022, 8904768.

[17] Uysal, F.; Köse, M.M. Classification of Breast Cancer Ultrasound Images with Deep Learning-Based Models. Eng. Proc. 2022, 31, 8.

[18] Ragab, M.; Albukhari, A.; Alyami, J.; Mansour, R.F. Ensemble deep-learning-enabled clinical decision support system for breast cancer diagnosis and classification on ultrasound images. Biology 2022, 11, 439.

[19] Xing, J.; Chen, C.; Lu, Q.; Cai, X.; Yu, A.; Xu, Y.; Huang, L. Using BI-RADS stratifications as auxiliary information for breast masses classification in ultrasound images. IEEE J. Biomed. Health Inform. 2020, 25, 2058–2070.

[20] Ragab, D.A.; Sharkas, M.; Marshall, S.; Ren, J. Breast cancer detection using deep convolutional neural networks and support vector machines. PeerJ 2019, 7, e6201.

[21] R. Golchha, P. Khobragade and A. Talekar, "Design of an Efficient Model for Health Status Prediction Using LSTM, Transformer, and Bayesian Neural Networks," 2024 International Conference on Innovations and Challenges in Emerging Technologies (ICICET), Nagpur, India, 2024, pp. 1-5, doi: 10.1109/ICICET59348.2024.10616353.

[22] Yu, X.; Wang, S.H. Abnormality diagnosis in mammograms by transfer learning based on ResNet18. Fundam. Inform. 2019, 168, 219–230.

[23] Islam, M.M.; Haque, M.R.; Iqbal, H.; Hasan, M.M.; Hasan, M.; Kabir, M.N. Breast cancer prediction: A comparative study using machine learning techniques. SN Comput. Sci. 2020, 1, 1–14.

[24] Alzubaidi, L.; Al-Shamma, O.; Fadhel, M.A.; Farhan, L.; Zhang, J.; Duan, Y. Optimizing the performance of breast cancer classification by employing the same domain transfer learning from hybrid deep convolutional neural network model. Electronics 2020, 9, 445.

[25] Gao, Y.; Geras, K.J.; Lewin, A.A.; Moy, L. New frontiers: An update on computer-aided diagnosis for breast imaging in the age of artificial intelligence. AJR Am. J. Roentgenol. 2019, 212, 300.