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BREAST CANCER DETECTION USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT:

Breast cancer is very common and is considered as the second dangerous disease all over the world due to its death rate. Accurate early detection can effectively reduce the mortality rate caused by breast cancer. Masses and micro calcification clusters are an important early signs of breast cancer. Micro Calcifications are tiny mineral deposits within the breast tissue. They look like small white spots on the pictures. They may or may not be caused by cancer. Masses can be many things, including cysts (fluid-filled sacs) and non-cancerous solid tumours, but they could also be cancer. Any mass that is not clearly a simple fluid-filled cyst usually needs to be biopsied. It is often difficult to distinguish abnormalities from normal breast tissues because of their subtle appearance and ambiguous margins. Accordingly the cancer can be classified as benign, malignant or normal. Neural networks is an interconnected collection of nodes called neurons or perceptrons. input data, typically one pixel of the image, and applies a simple computation, called an activation function to generate a result. Our project aims at subjecting the obtained mammogram/sonogram to certain filtering techniques and algorithms to acquire details about the presence/absence of tumour cells and then providing its outline. It also aims at differentiating between benign and malignant stages of cancer. We are going to use Wiener and CLAHE filtering techniques to enhance the obtained mammogram.

INDEX TERMS: Convolutional Neural Networks, Morphological Operations,Erosion and Dilation

INTRODUCTION:

CONVOLUTIONAL NEURAL NETWORKS:

The name “Convolutional Neural Network” indicates that the network employs a mathematical operation called ”convolution”. Convolution is a

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Convolutional networks are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers.

A convolutional neural network consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of a series of convolutional layers that convolve with a multiplication or other dot product. The activation function is commonly a RELU layer, and is subsequently followed by additional convolutions such as pooling layers, fully connected layers and normalization layers, referred to as hidden layers because their inputs and outputs are masked by the activation function and final convolution.

Though the layers are colloquially referred to as convolutions, this is only by convention. Mathematically, it is technically a sliding dot product or cross-correlation. This has significance for the indices in the matrix, in that it affects how weight is determined at a specific index point.

A ConvNet takes an image expressed as an array of numbers, applies a series of operations to that array and, at the end, returns the probability that an object in the image belongs to a particular class of objects. For instance, a ConvNet can let you know the probability that a photo you took contains a building or a horse or what have you. It might be used to distinguish between very similar instances of something. For example, you could use a ConvNet to go through a collection of images of skin lesions and classify the lesions as benign or malignant.

Applications of CNN:

Simple applications of CNNs which we can see in everyday life are obvious choices, like facial recognition software, image classification, speech recognition programs, etc.

EXISTING METHODOLOGY:

3. Tumour Detection in Automated Breast Ultrasound using 3D CNN and Prioritised Candidate Aggregation

This section provides the details of the existing methods of Breast Cancer Detection using 3D CNN and Prioritised Candidate Aggregation. The proposed detection algorithm takes as parameters a list of target tumour sizes (*Ls*) and the degree of aggregation (*DoA*). The algorithm involves three main stages:

- VOI extraction
- Tumour probability estimation with the 3-D CNN
- Candidate aggregation.

At first, an efficient 3-D sliding window method is used to extract the VOIs. Then, the 3-D CNN is used to estimate the probability being tumour of each VOI, and the VOIs with tumour probability greater than the threshold than a threshold are selected as tumour candidates. However, some of the candidates may overlap each other. Hence, a candidate aggregation method based on the hierarchical clustering is proposed to combine the overlapped candidates into a single tumour box, where each candidate is scheduled with different priority for alleviating the over aggregation problem. Finally, to detect

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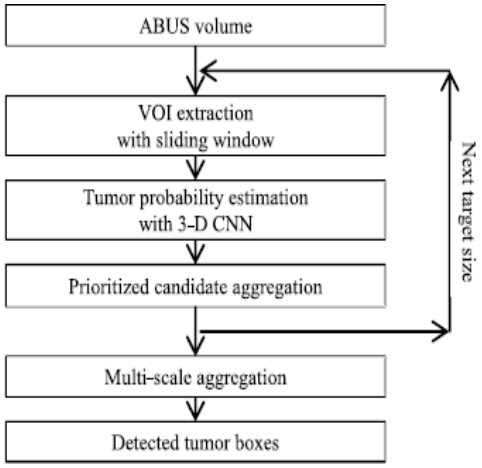
lesions of different sizes, the aforementioned steps are performed multiple times at different scales, and a simple scheme is adopted for multiscale tumour VOI aggregation.



Schematic flowchart of the proposed CAD system

VOI extraction with Sliding Window:

VOI stands for Volume Of Interest. For VOI extraction, the first step of our CAD system employs the 3-D sliding window to scan the whole ABUS Volume. When the sliding window moves with a stride, a VOI will be extracted. For a target size L, our CAD system uses the stride L to extract VOIs of size $2L$ for the following reason. Although the tumour can be entirely covered with higher probability using a small stride, the number of extracted VOIs will be very large. In fact, a tumour of size less than or equal to L is guaranteed to be completely covered by at least one VOI using a sliding window of size $2L$ and stride $\leq L$. Therefore, the settings will reduce the execution time while simultaneously produce VOIs covering the entire target tumours. Furthermore, since the 3-D CNN requires inputs of the same dimension, each VOI will be rescaled.

Tumour Probability Estimation with 3-D CNN:

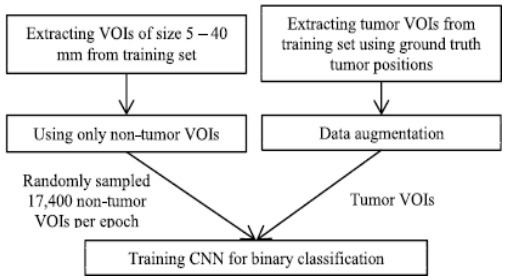


Fig.3.2Flowchart of training CNN.

After the VOI extraction, each VOI will be estimated the probability being tumour by the CNN. One way to deal with 3-D data is to use 2-D CNN to predict each 2-D slice, and combine the results using recurrent neural network techniques such as long short-term memory (LSTM). The 3-D CNN has the ability to extract 3-D features, which more directly include information of relationship between adjacent voxels from arbitrary directions. Therefore, 3-D CNN is adopted in this study. As to the CNN architecture, several complicated designs such as Alex Net, VGGNet-16 and ResNet-34 had been proposed and showed excellent results in classification of natural images. However, the 3-D versions of those deep neural network models contain too many parameters, and the processing time will increase dramatically. Since medical data meet certain acquisition

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criteria a CNN with less trainable parameters suffices. Therefore, a simplified 3-D CNN architecture was designed in this study. The outputs of the second and fourth convolutional layers are down-sampled by the following 2×2×2 max-pooling layers. The objective of max pooling is to reduce computational cost and over-fitting by providing a more abstracted form of the input image. In second max-pooling layer, the outputs connect to a neural network consisting of three fully-connected (FC) layers for binary classification. It behaves as a regularizer by preventing neurons from co-adapting to each other. In artificial neural networks, the activating function of a neuron defines the output of that neuron given an input or set of inputs. The rectified linear units (ReLU) [27], defined as $f(x) = \max(0, x)$, have been widely used as activating function for additional speed-ups, as opposed to conventional function such as sigmoid and hyperbolic tangent functions. However, the dying ReLU problem will occur when a ReLU neuron is pushed into a state in which the gradient becomes zero. The leaky rectified linear units (Leaky ReLU) is a variant of ReLU to cope with this problem by introducing a small slope when the neuron is not active. The Leaky ReLU is defined as $f(x) = \max(0, x) + \alpha \cdot \min(0, x)$, where α is the leakage coefficient. Except for the output layer with sigmoid function for binary classification, all the other layers use Leaky ReLU as the activating functions.

Training the 3D CNN:

In order to train the 3-D CNN, the VOIs of tumour and non-tumour class have to be provided. A VOI of any size extracted from anywhere in the ABUS can be assigned to non-tumour class as long as it satisfies the following two conditions. First, the center of the VOI is not included by any ground truth tumour box. Second, the VOI does not include the center of any tumour. In this study, the sizes of the extracted non-tumour VOIs are randomly selected in the range from 5 to 40 mm. For the tumour class, however, it is unsuitable to simply use those VOIs that failed to be assigned to non-tumour as tumour VOIs, because many of these VOIs exhibit less essential tumour characteristics. For instance, these VOIs may crop the tumour overmuch, or only cover a small part of the tumour. Training the network with the most representative data conforming to the features for each class can decrease the convergence time and improves the generalization ability. Hence, instead of using the VOIs extracted by the sliding window, the ground truth tumour positions and sizes were used to accurately extract the tumour VOIs to train the 3-D CNN. The size of the tumour VOIs is two times the size of the tumour, which is consistent with the relative size between the target tumours and the sliding window. Only one 3-D CNN was trained using all tumour and non-tumour VOIs of all sizes. In addition, since the number of tumour VOIs is much less than that of non-tumour VOIs, data augmentation is applied to the tumour VOIs. Data augmentation not only increases the number of training data but also

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improves the robustness and generalization of the CNN. Therefore, 100 times of shifting (± 20%) relative to the VOI size along three orthogonal axes), scaling (±20%), and flipping (along superior-inferior and left right directions) are randomly applied to each tumour VOI.

Prioritised Candidate Aggregation:

After tumour probability estimation using the 3-D CNN, the tumour candidates are selected from VOIs with probability higher than a threshold *TH*. However, a tumour will probably be covered by multiple overlapped candidates. The overlapped candidates should be aggregated into a single box. Therefore,
a candidate aggregation algorithm based on the hierarchical clustering (HC) is proposed. In HC, a linkage criterion, which is a function of dissimilarity metric, is used as the measure of dissimilarity between data sets. Two sets with dissimilarity less than a threshold will be combined into a cluster. The input
of HC is the centers of tumour candidates and the parameters are listed in Table V. The HC will assign neighbouring centers into a cluster. The dissimilarity threshold used in HC is set to 3 *L*, since the longest Euclidean distance between the centers of two VOIs of size 2*L* covering a tumour of size $\leq L$ is$\sqrt{3}\,L$. After clustering, the weighted average with the positions of candidates in the same cluster is computed and used as the position of the aggregated box where the weight assigned to each candidate is its estimated tumour probability. The size of the aggregated box remains 2*L*.

PARAMETERS OF HIERARCHICAL CLUSTERING

Parameter	Value
Dissimilarity metric	Euclidean distance $d(a,b)=\sqrt{\sum_i (a_i-b_i)^2}$
Linkage criterion	Single-linkage (nearest neighbor) $\min(d(a,b): a \in A, b \in B)$
Dissimilarity threshold	$\sqrt{3}L$

Fig3.3 Parameters of Hierarchical Clustering

Alleviation of Over-Aggregation:

When a lower threshold *TH* is applied for candidate selection, lots of candidates will emerge and densely distribute everywhere around the ABUS volume. As a result, the nearest neighbour criterion used in HC will group too many candidates into a cluster. Hence, a tumour box may be displaced from correct tumour position and cover the tumour incompletely. To address the issue, the cluster size (i.e. the number of candidates in a cluster) must be restricted
and the candidates with higher tumour probabilities should be prioritized for aggregation. In particular, the highest threshold $TH\_ > TH$ is first applied for candidate selection followed by the HC. Then, *TH´* is slightly decreased to select more candidates. However, a newly selected candidate will join its neighbouring cluster only if the cluster has not reached the maximal size yet, where the maximal cluster size is referred to as degree of aggregation (*DoA*) in our algorithm. Because a tumour of size less than *L* will be entirely covered by at most eight VOIs

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of size 2*L*, the optimized *DoA* should be no more than eight. Candidate selection and clustering are repeated for each *TH´* until *TH´* equals *TH*.

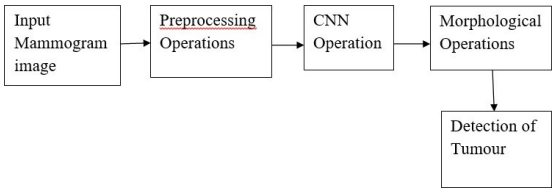
Multi-Scale Aggregation:

Because the above procedure only handles a single target tumour size *L*, our system allows the physician to input multiple target tumour sizes (multiple *L*s) and the same procedure will be performed multiple times on each target size for multi-scale tumour detection. As a consequence, the tumour boxes of multiple sizes may be produced and overlap each other. Since each tumour box has been obtained by aggregating multiple candidates, the maximal probability of the candidates within a cluster is used to represent the tumour probability of the aggregated tumour box. If a larger tumour box covers the centers of any smaller boxes, they will be aggregated using the weighted average with both the positions and sizes where the weights are the tumour probabilities.

PROPOSED METHODOLOGY:

The proposed work helps to detect and locate the position of the tumour. We use the operations of preprocessing to prepare the image, convolution can take in an input image, assign importance to various aspects/objects in the image and be able to differentiate one from the other and morphological operations such as erosion and dilation to process the pixels.

BLOCK DIAGRAM:



Block Diagram of the proposed methodology

Input Mammogram Image:

A mammogram is an X-ray picture of the breast. Doctors use a mammogram to look for early signs of breast cancer. It is given as an input for the operation.

Preprocessing Operations:

Digital image processing can be defined as processing of digital image in a digital manner using a digital device like computer or others. The digital image processing is getting more and more importance application areas, nowadays because of its two major

1. Improvement of pictorial information for human interpretation.

2. Processing of image data for storage, transmission and representation for autonomous machine perception.

The aim of preprocessing techniques is to improve the image data to suppress the unwanted distortions and to enhance some features of the input image.

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In medical image processing, preprocessing of an image is very important so that the extracted image does not have any impurities, and it is accomplished to be better for the forthcoming process such as segmentation, feature extraction, etc. Only the correct segmentation of the tumour will yield the accurate result.

The preprocessing techniques used here are

1. **Wiener filter**
2. **Clahe filters.**

Wiener filter:

It is used to produce an estimate of a desired or target random process by linear time-invariant (LTI) filtering of an observed noisy process, assuming known stationary signal and noise spectra, and additive noise. The goal of the Wiener filter is to compute a statistical estimate of an unknown signal using a related signal as an input and filtering that known signal to produce the estimate as an output. For example, the known signal might consist of an unknown signal of interest that has been corrupted by additive noise. The Wiener filter can be used to filter out the noise from the corrupted signal to provide an estimate of the underlying signal of interest. The Wiener filter is based on a statistical approach. Typical deterministic filters are designed for a desired frequency response. However, the design of the Wiener filter takes a different approach. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the linear time-invariant filter whose output would come as close to the original signal as possible.

Here the image and noise are considered as random variables and the objective is to find an estimate $\hat{f}$ of the uncorrupted image f such that mean square error between them is minimised.

$$\hat{f}(x) = \sum_{S=-\infty}^{\infty} h_w(x-s)\, g(s)$$

This error measure is given by,

$$e^2 = E\left\{(f-\hat{f})^2\right\}$$

Assuming that the noise and the image are uncorrelated ,the minimum error function of the above expression is given in the frequency domain by the expression,

$$\hat{F}(u,v) = \left[\frac{H^*(u,v)\, S_f(u,v)}{S_f(u,v)\,|H(u,v)|^2 + S_\eta(u,v)}\right] G(u,v)$$

$$= \left[\frac{H^*(u,v)}{|H(u,v)|^2 + S_\eta(u,v)/S_f(u,v)}\right] G(u,v)$$

$$= \left[\frac{1}{H(u,v)}\,\frac{|H(u,v)|^2}{|H(u,v)|^2 + S_\eta(u,v)/S_f(u,v)}\right] G(u,v)$$

H (u,v) = Fourier transform of degradation function

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H*(u,v) = Complex conjugate of H (u,v)

$|H(u,v)|^2 = H^*(u,v)\, H(u,v)$

$S_\eta = |N(u,v)|^2$ = power spectrum of noise

$S_f = |F(u,v)|^2$ = power spectrum of the undegraded image

G (u,v) = Fourier transform of the degraded image.

CLAHE Filter:

CLAHE stands for **C**ontrast **L**imited **A**daptive **H**istogram **E**qualizer.

Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images. It differs from ordinary histogram equalization in the aspect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image .However, AHE has a tendency to over-amplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called **Contrast Limited Adaptive Histogram Equalization** (CLAHE) prevents this by limiting the amplification.

Contrast Limited AHE (CLAHE) is a variant of adaptive histogram amplification is limited, so as to reduce this problem of noise amplification. In CLAHE, the contrast amplification in the vicinity of a given pixel value is given by the slope of the transformation function. This is proportional to the slope of the neighbourhood cumulative distribution function (CDF) and therefore to the value of the histogram at that pixel value. CLAHE limits the amplification by clipping the histogram at a predefined value before computing the CDF. This limits the slope of the CDF and therefore of the transformation function. The value at which the histogram is clipped, the so-called clip limit, depends on the normalization of the histogram and thereby on the size of the neighbourhood region. Common values limit the resulting amplification to between 3 and 4. It is advantageous not to discard the part of the histogram that exceeds the clip limit but to redistribute it equally among all histogram bins.

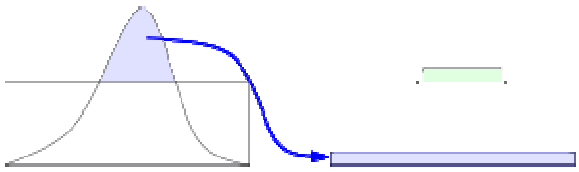

Fig 4.2 Excess redistribution in CLAHE technique.

redistribution will push some bins over the clip limit again (region shaded green in the figure), resulting in an effective clip limit that is larger than the prescribed limit and the exact value of which depends on the image. If this is undesirable, the redistribution

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procedure can be repeated recursively until the excess is negligible.

4.1.3 CNN Operation:

The name "Convolutional Neural Network" indicates that the network employs a mathematical operation called "convolution". Convolution is a specialized kind of linear operation. Convolutional networks are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers.

A convolutional neural network consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of a series of convolutional layers that convolve with a multiplication or other dot product. The activation function is commonly a RELU layer, and is subsequently followed by additional convolutions such as pooling layers, fully connected layers and normalization layers, referred to as hidden layers because their inputs and outputs are masked by the activation function and final convolution.

Though the layers are colloquially referred to as convolutions, this is only by convention. Mathematically, it is technically a sliding dot product or cross-correlation. This has significance for the indices in the matrix, in that it affects how weight is determined at a specific index point.

A ConvNet takes an image expressed as an array of numbers, applies a series of operations to that array and, at the end, returns the probability that an object in the image belongs to a particular class of objects. For instance, a ConvNet can let you know the probability that a photo you took contains a building or a horse or what have you. It might be used to distinguish between very similar instances of something. For example, you could use a ConvNet to go through a collection of images of skin lesions and classify the lesions as benign or malignant.

Layers used to build ConvNets:

A simple ConvNet is a sequence of layers, and every layer of a ConvNet transforms one volume of activations to another through a differentiable function. We use three main types of layers to build ConvNet architectures:

- Convolution Layer
- Pooling Layer
- Fully Connected Layer

We will stack these layers to form a full ConvNet architecture.

Convolution Layer: The Convolution layer is the core building block of a Convolutional Network that does most of the computational heavy lifting. The CONV layer's parameters consist of a set of learnable filters. Every filter is small spatially (along width and height), but extends through the full depth of the input volume. For example, a typical filter on a first layer of a ConvNet might have size 5x5x3 (i.e. 5 pixels width and height, and 3 because images

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have depth 3, the colour channels). During the forward pass, we slide (more precisely, convolve) each filter across the width and height of the input volume and compute dot products between the entries of the filter and the input at any position. As we slide the filter over the width and height of the input volume we will produce a 2-dimensional activation map that gives the responses of that filter at every spatial position. Intuitively, the network will learn filters that activate when they see some type of visual feature such as an edge of some orientation or a blotch of some colour on the first layer, or eventually entire honeycomb or wheel-like patterns on higher layers of the network. Now, we will have an entire set of filters in each CONV layer (e.g. 12 filters), and each of them will produce a separate 2-dimensional activation map. We will stack these activation maps along the depth dimension and produce the output volume.

Local Connectivity: When dealing with high-dimensional inputs such as images, as we saw above it is impractical to connect neurons to all neurons in the previous volume. Instead, we will connect each neuron to only a local region of the input volume. The spatial extent of this connectivity is a hyper parameter called the **receptive field** of the neuron (equivalently this is the filter size). The extent of the connectivity along the depth axis is always equal to the depth of the input volume. It is important to emphasize again this asymmetry in how we treat the spatial dimensions (width and height) and the depth dimension: The connections are local in space (along width and height), but always full along the entire depth of the input volume.

Spatial arrangement: We have explained the connectivity of each neuron in the Convolution Layer to the input volume, but we haven't yet discussed how many neurons there are in the output volume or how they are arranged. Three hyper parameters control the size of the output volume: the **depth, stride** and **zero-padding**. We discuss these next:

1. First, the **depth** of the output volume is a hyper parameter: it corresponds to the number of filters we would like to use, each learning to look for something different in the input. For example, if the first Convolutional Layer takes as input the raw image, then different neurons along the depth dimension may activate in presence of various oriented edges, or blobs of colour. We will refer to a set of neurons that are all looking at the same region of the input as a **depth column** (some people also prefer the term *fibre*).
2. Second, we must specify the **stride** with which we slide the filter. When the stride is 1 then we move the filters one pixel at a time. When the stride is 2 (or uncommonly 3 or more, though this is rare in practice) then the filters jump 2 pixels at a time as we slide them around. This will produce smaller output volumes spatially.
3. As we will soon see, sometimes it will be convenient to pad the input

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volume with zeros around the border. The size of this **zero-padding** is a hyper parameter. The nice feature of zero padding is that it will allow us to control the spatial size of the output volumes (most commonly as we'll see soon we will use it to exactly preserve the spatial size of the input volume so the input and output width and height are the same).

Pooling Layer:

It is common to periodically insert a Pooling layer in-between successive Convolution layers in ConvNet architecture. Its function is to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network, and hence to also control overfitting. The Pooling Layer operates independently on every depth slice of the input and resizes it spatially, using the MAX operation. The most common form is a pooling layer with filters of size 2x2 applied with a stride of 2 downsamples every depth slice in the input by 2 along both width and height, discarding 75% of the activations. Every MAX operation would in this case be taking a max over 4 numbers (little 2x2 region in some depth slice). The depth dimension remains unchanged. More generally, the pooling layer:

- Accepts a volume of size W1×H1×D1W1×H1×D1
- Requires two hyper parameters:
  - their spatial extent FF,
  - the stride SS,
- Produces a volume of size W2×H2×D2W2×H2×D2 where:
  - W2=(W1−F)/S+1W2=(W1−F)/S+1
  - H2=(H1−F)/S+1H2=(H1−F)/S+1
  - D2=D1D2=D1
- Introduces zero parameters since it computes a fixed function of the input
- For pooling layers, it is not common to pad the input using zero-padding.

It is worth noting that there are only two commonly seen variations of the max pooling layer found in practice: A pooling layer with F=3,S=2F=3,S=2 (also called overlapping pooling), and more commonly F=2,S=2F=2,S=2. Pooling sizes with larger receptive fields are too destructive.

Fully Connected layer:

Fully connected input layer (flattens) takes the output of the previous layers, "flattens" them and turns them into a single vector that can be an input for the next stage. **The first fully connected layer** takes the inputs from the feature analysis and applies weights to predict the correct label. **Fully connected output layer** gives the final probabilities for each label.

The objective of a fully connected layer is to take the results of the convolution/pooling process and use them to classify the image into a label (in a simple classification example).The output of convolution/pooling is flattened into a

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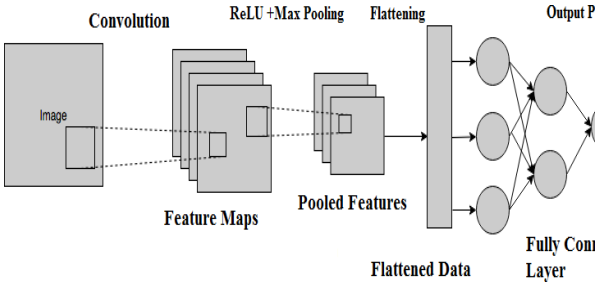
single vector of values, each representing a probability that a certain feature belongs to a label. For example, if the image is of a cat, features representing things like whiskers or fur should have high probabilities for the label "cat". The image below illustrates how the input values flow into the first layer of neurons. They are multiplied by weights and pass through an activation function (typically ReLu), just like in a classic artificial neural network. They then pass forward to the output layer, in which every neuron represents a classification label. The fully connected part of the CNN network goes through its own back propagation process to determine the most accurate weights. Each neuron receives weights that prioritize the most appropriate label. Finally, the neurons "vote" on each of the labels and the winner of that vote is the classification decision.



Working of the layers in CNN

If the CNN operation detects the presence of tumour ,then it proceeds to the morphological operations if not the operation is stopped here itself.

Morphological Operation:

Morphology is a broad set of image processing operations that process images based on shapes. Morphological operations apply a structuring element to an input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbours. The most basic morphological operations are dilation and erosion. **Dilation** adds pixels to the boundaries of objects in an image, while **Erosion** removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the *structuring element* used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbours in the input image.

The rule used to process the pixels defines the operation as dilation or erosion.

Rules for dilation:

The value of the output pixel is the *maximum* value of all pixels in the neighbourhood. In a binary image, a pixel is set to `1` if any of the neighbouring pixels have the value1. Morphological dilation makes objects more visible and fills in small holes in objects.

Rules for erosion:

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The value of the output pixel is the *minimum* value of all pixels in the neighbourhood. In a binary image, a pixel is set to 0 if any of the neighbouring pixels have the value 0.Morphological erosion removes islands and small objects so that only substantive objects remain.

Morphological Dilation of a Grayscale Image

Dilation and erosion are often used in combination to implement image processing operations. For example, the definition of a morphological *opening* of an image is erosion followed by dilation, using the same structuring element for both operations. You can combine dilation and erosion to remove small objects from an image and smooth the border of large objects.

Detection of tumour:

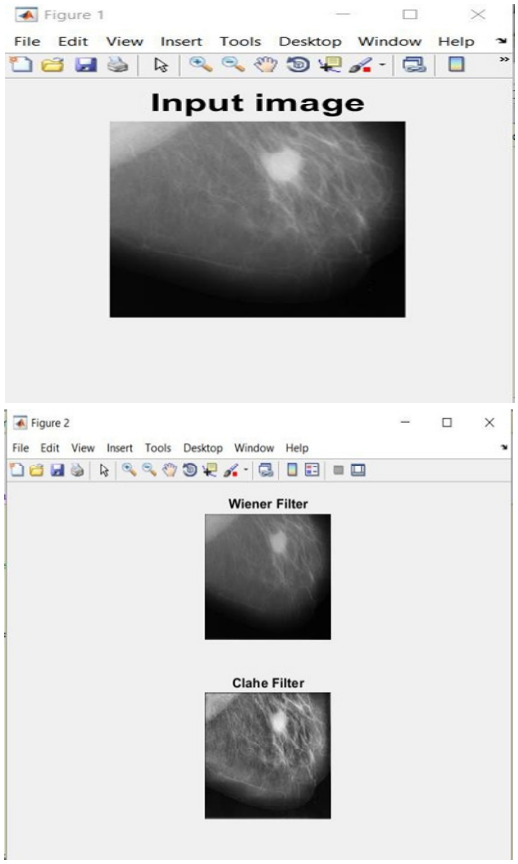
Thus a clear outline of the detected tumour is obtained by combining all the above processes. A mammogram is given as input and pre-processed using Wiener and CLAHE filters. Then CNN is performed on the image and found out if the image is a normal one or it is the abnormal with the presence of tumour. If tumour is detected then the tumour part is outlined using Morphological operations. If not then the output of the dialog box is shown as "NO tumour". This is how this process works. Let us have a look at the pictorial representation of this working in a flowchart.

RESULT:

Testing a tumour image:

Input image:

Preprocessed image:



Filtered image:

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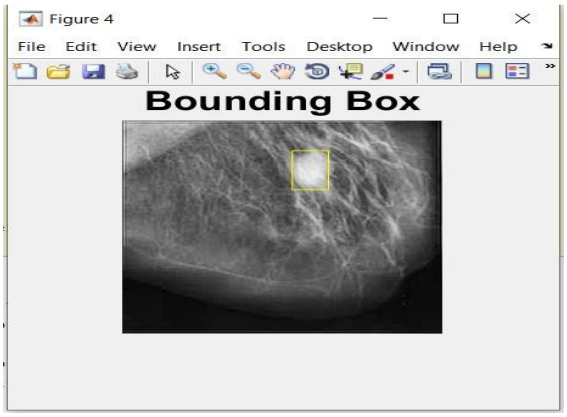
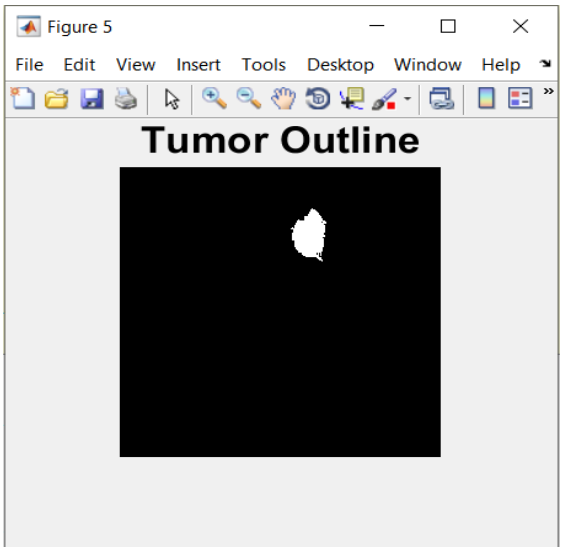
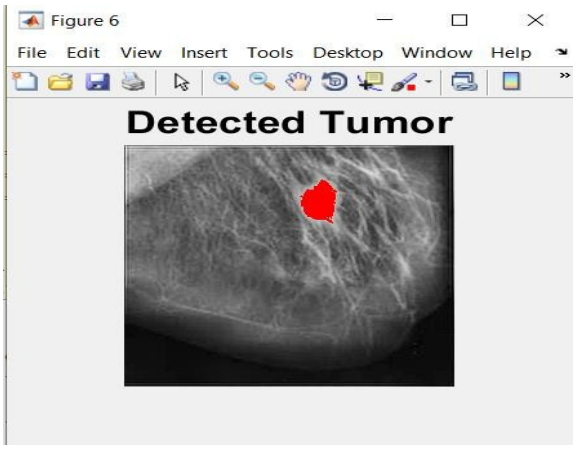




Highlighting the tumour:
Final Output:



CONCLUSION:

We have designed a Breast Cancer Detection System which not only identifies cancer cells but also provides a clear outline of the affected areas. This is a simple cancer detection system which doesn't involve any costly components or any time consuming process. It outperforms the existing systems by the usage of lesser components and providing an efficient output. The localization of the tumour helps in effective treatment in the future. The higher the number of training samples used, higher are the chances of correct detection. Our further work would include the usage of Capsule Networks which overcomes the disadvantages of a typical Convolutional Neural Network. Capsules at one level make predictions, via transformation matrices and using other algorithms. When multiple of predictions agree, a higher level capsule becomes active. A Capsule is a group of neurons whose vector represents the parameter instance of a very specific type of entity which can be termed as an object or a part of an object. The length of an activity vector is used to represent the probability that an entity exists and its orientation to represent the instantiation parameters. A capsule network aims to mimic the biological neuron organization which makes it more suitable for medical image processing systems.

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