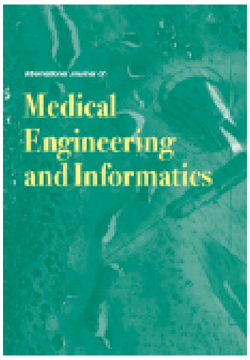


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# Breast cancer diagnosis by hybrid fuzzy CNN network

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# Breast cancer diagnosis by hybrid fuzzy CNN network

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**Abstract:** Breast cancer is a common gynaecological ailment that affects women all over the world. Early identification of this disease has been shown to be extremely beneficial in terms of therapy. Mammographic pictures are analysed in this article utilising image processing methods and a pipeline structure to see whether they contain malignant tumours, which are subsequently categorised. The SVM classifier is used for classification, and it is fed by the characteristics that have been picked. It is supported by a number of kernel functions. This differs from standard machine learning classification and optimisation strategies, and it is shown in a unique manner. The outcomes of

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the actualised computer-aided diagnostic (CAD) learning process are analysed in order to determine whether or not it was successful. The BCDR-F03 dataset is evaluated, as well as the: 1) local mammographic dataset; 2) colony optimisation-based multi-layer perceptron (ACO-MLP) dataset.

**Keywords:** breast cancer; deep learning; convolution neural network; CNN; prediction; benign and malignant; computer-aided diagnostic; CAD.

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## 1 Introduction

As the most common kind of cancer in women, breast cancer ranks first among the primary causes of cancer-related mortality. In breast cancer, cells that are located in the same organ as the patient are transformed into a malignant tumour that spreads to other organs. Before dying, the illness starts in the lobules or breast ducts and spreads via the glands' ducts and walls, damaging the surrounding adipose tissue and even other parts of the body. The majority of breast cancers develop in the parts of milk-producing organs known as lobules, as well as the channels that connect the lobules and eventually reach the nipple. The breast contains a variety of tissues, including fatty, connective, and lymphatic tissues (American Cancer Society, 2015). Breast illness is the most deadly of all forms of malignant development since it has progressed at the fastest rate, accounting for 22% of all new cases every year, according to the American Cancer Society. Because there are no specific methods for preventing this disease, accurately identifying the presence of a tumour and the type of cancerous tumour would play a critical role in influencing doctors' decisions about applying true treatment methods and, as a result, in restoring the lives of people (Cheng et al., 2010). Several causes might cause a person's predisposition to deteriorate; among them is breast cancer, which is becoming an increasingly common cause of mortality among women. As a result, it is of primary interest to reduce the mortality rate by identifying diseases as soon as they occur. Breast cancer, on the other hand, is defined as the uncontrolled proliferation of abnormal cells in the breast's milk-secreting glands. Early detection (Sivakumar and Kumar, 2019) is the most effective technique for reducing the number of fatalities caused by breast cancer. Early identification of breast cancer (Lee et al., 2022) requires a precise and reliable diagnostic formula that enables doctors to discriminate between benign and malignant breast tumours without resorting to a rapid surgical sample to confirm the diagnosis. This kind of detection is based on the notion of assigning patients to one of two groups: either one of the 'benign' clusters or one of the 'malignant' clusters (Peng et al., 2022). A small spine objective biopsy is a very easy and rapid method of detecting malignant growth in the spine, which may then be used to guide cancer therapy.

In this approach, a sample of material or fluid from a nodule is collected and then examined under a microscope (Qiao et al., 2022) to determine whether or not the tissues are healthy. If the knob cannot be felt, visualisation techniques must be used to determine the precise location of the knob's position. A medical professional uses an ultrasound (Khalil et al., 2020) to inspect the spine and aim it toward the affected area in the ultrasound technique. In order to uncover significant qualities that distinguish one input picture from another, this neural network system evaluates input images by extracting suigtraining weights and biases. The convolution neural network (CNN) is a deep-learning neural network that learns from experience (Khan et al., 2018). A diagnostic tool may be constructed utilising CNNs in order to categorise different kinds of thermograms into 'healthy' and 'with-tumour' categories without the need for the assistance of human specialists. In the early investigations of CNN, segmentation was shown to be a critical component of image recognition. There are several research devoted to various techniques of picture recognition, including studies (Antonini et al., 2015; Dayakshini, 2015; Kermani et al., 2015), which are listed here. CNN is a feed-forward artificial neural network in computer vision that has been effectively used in a variety of computer vision applications for decades (Lecun et al., 2015, 1998). Internally, a new version of black propagation boosting recurrent Wienmed (BPBRW) has been implemented to discover breast cancer.

In recent years, the availability of processing resources and devices has made it possible to train CNNs with a large number of layers, (i.e., the deep CNN) with a high degree of accuracy. Deep CNNs were possibly used for the first time in image identification in the ImageNet competition (Russakovsky et al., 2015), which took place back in 2012. It has now achieved significant use in many applications, comprising natural language processing, image segmentation, and medical imaging analysis (Tajbakhsh et al., 2016; Li et al., 2014). The huge amount of trainable properties that can be identified at different layers of a deep CNN is the core strength of this kind of neural network (Eigen et al., 2013). For the identification of breast cancer, a knowledge-based system based on fuzzy logic was built, with the data being grouped using the maximising approach. It was feasible to remove the problem of multicollinearity with the aid of principal component analysis (Nilashi et al., 2017).

## 2 Related works

An initial study into the development and optimisation of machine learning models for full image categorisation mammography is presented in this publication. The researcher tested seven alternative CNN designs and concluded that using a CNN in conjunction with data augmentation and transfer learning methods is the most effective way to improve classification performance. The number of cancer sufferers worldwide is expanding at an alarming pace. According to the World Health Organization (WHO), breast cancer affects around 2.1 million people worldwide each year.

As per the National Cancer Institute, women died of breast cancer in 2018, accounting for roughly 15% of all cancer-related deaths among women (Senthil Kumar and Kumutha, 2020). Figure 1 depicts the data information on cancer diagnoses and cancer fatalities in the USA in 2019 (Costa et al., 2018). It is critical to discover the illness early and provide excellent treatment. A precise and dependable diagnostic strategy is essential for early diagnosis to be successful. Despite the fact that mammography is one of the most common and commonly utilised techniques for identifying breast cancer, it is also one of the most costly. As a result, systematic mammography screening of the female population, as well as the early detection of early-stage breast cancer, may enhance the survival prospects of patients while also lowering the harmful effects of the medicines that must be delivered. Specifications are provided in Figure 1.

Within recent decades, there has been an explosion of computer-aided diagnostic (CAD) research in malignant breast development, which has included nurturing and developing intelligent systems to increase cluster performance (Jiao et al., 2016; Li et al., 2017; Berment et al., 2014; Chougrad et al., 2018; Jiang et al., 2014). Different CAD diagnostic methods for breast cancer have revealed that the detection rate has increased from 4.7% to 19.5% when compared to radiologists. In order to investigate the irregularities in mammograms, many automated approaches have been developed and put to use. However, the most significant disadvantage of modern CAD breakthroughs in terms of calcifications is the massive volume of false positives created by these technologies. A significant percentage of the study is focused mostly on the poor discovery specificity of the compounds. It is often used as an argument in favour of computerised illness diagnosis. Rather than increasing the number of fresh mass location calculations that provide great malignant growth finding findings, a few studies are being performed to attempt to lower the frequency of FP. In another instance, Supriya and Deepa (2019) created an optimised artificial neural network (OANN) for the purpose of detecting illness in a patient. The main advantage of this suggested model is that it has needed less energy to conduct the process than previous models. However, in order to get the greatest results, less energy has been used throughout the process's execution.

Junior et al. (2019) created the algorithms multi-verse optimiser (MVO) and gradient boosting decision tree (GBDT) to differentiate benign and malignant breast tumours. The technique was developed with the goal of distinguishing between benign and malignant forms of breast cancer. At the end of the process, the major factors are computed and compared to previous work, with a small margin of error being indicated. However, it has resulted in an increase in the quantity of energy used. A DL-aided effectual Adaboost algorithm (DLA-EABA) has been created by Zheng et al. (2020) to identify breast cancer at an earlier stage in order to lower the mortality rate.

## 3 System models – methodology

Thermal pictures were extracted from the publicly available Visual Lab database (2014), which comprises around 287 thermal images, and utilised as input for our diagnostic programme. Nevertheless, only 76 thermal pictures were chosen as the most acceptable for the current investigation. These thermal pictures were accompanied by a diagnosis from a doctor and were available in three different views: frontal, left, and right. The scientists also utilised a second database that included thermograms taken from patients at the 'multifunctional medical centre', which they had collected via their research.

The thermal photographs that were the most relevant for this project were selected from a pool of 38 that were submitted for consideration. Breast thermograms taken by women between the ages of 18 and 80 are included in the current edition of the database.

Breast thermograms have been named in such a manner that each photo in the database has a unique name, in order to protect the anonymity of those who have had the procedure. A standard breast thermogram contains three RGB channels and a square size of 224, 224, 3 pixels, which is the amount of pixels in one square inch. In order to properly assess the whole breast tissue and adjacent ganglion groups, a breast thermogram should encompass half of the armpit. When compared to the temperature in the surrounding area of interest, the region of interest on the breast thermogram for a patient with breast cancer demonstrates a statistically significant increase in temperature. Figure 1 depicts several examples of thermograms that have been utilised.

**Figure 1** Segmentation and classification of thermal images into 'sick' and 'healthy' (see online version for colours)

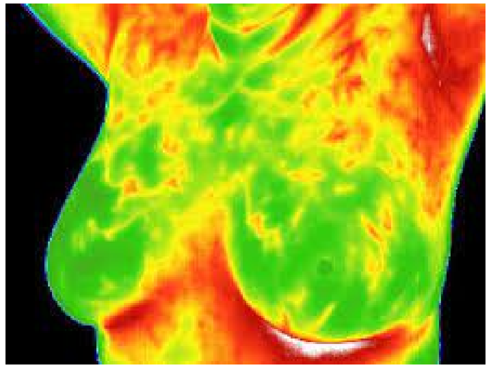
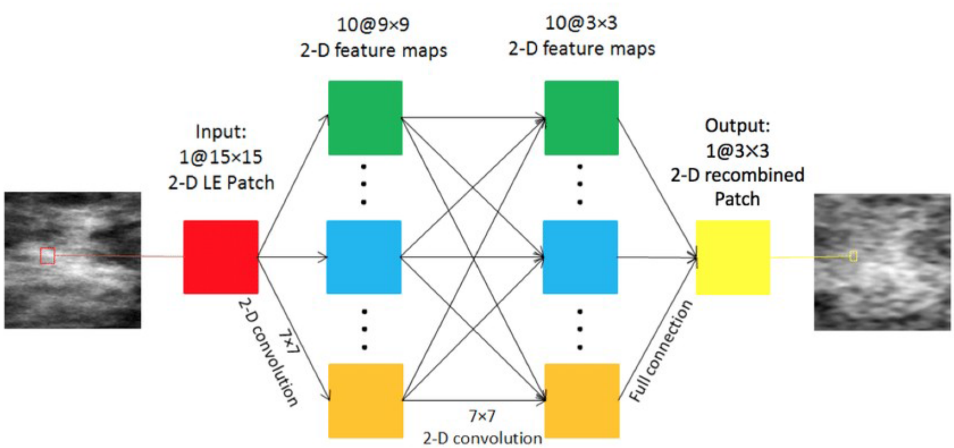


Image classification is the process of categorising photos based on their visual content, such as colour or shape. It is necessary to recognise breast thermograms with specified labels, such as healthy and unwell, in order for neural networks to learn how to recognise them. Supervised learning is the term used to describe this issue (Simeone, 2018). The images were separated into two categories: 'healthy' and 'sick' for the purposes of the present research. For breast cancer research, it is advised that a shallow-deep CNN (SD-CNN) be employed in order to properly study the advantages of CNNs and CEDM, as well as their limitations (Figure 2). In order to begin, we utilise CEDM to generate a shallow-CNN in order to detect the connections between the images. FFDM is then applied to the shallow-CNN resulting in the creation of 'virtual' recombined images in a virtual environment.

**Figure 2** The architecture of shallow-deep CNN 3.1 image pre-processing (see online version for colours)



### 3.1 Image pre-processing

The boundaries between medical images have become increasingly blurred. This is one of the reasons why pre-processing methods are significant. It is thus necessary to undertake pre-processing procedures after getting the input information from the medical pictures, which are techniques for eliminating noise and isolating and improving the distinction of places where there is a chance of numerical information.

### 3.2 Image contrast – improvement

There are numerous types of contrast difficulties that often occur in photographs, including incorrect lighting and room settings, a lack of sufficient applicant interface for photography, and a lack of enough quality in the measuring sensors and equipment. These factors will be eliminated with the removal of certain critical information, the darkening or overexposure of the picture, and eventually the appearance of image anomalies. The existence of these factors raises the requirement for image enhancement in a variety of medical imaging a result of their presence. The absence of these criteria in the vast majority of medical photographs raises the need for improvement. In order to achieve this improvement, contrast enhancement has been used. A straightforward application for doing a piecewise linear contrast stretch function on a digital picture. An eight-bit lookup table is used in this research to increase the contrast of pictures that are subsequently recorded on a disc. This is accomplished by the use of the following formula:

$$y_{hist} = \frac{x_{hist} - Min_{hist}}{Max_{hist} - Min_{hist}}, \tag{1}$$

$x_{hist}$ and $y_{hist}$ signify the input image before and after contrast enhancement.

### 3.3 Noise reduction

As previously stated, different situations in medical imaging result in various types of noise in the images, which must be eliminated before the images can be processed further. This is accomplished via the use of noise reduction. White noise, random noise, and Gaussian noise are all possible types of noise. Noise is often observed in the high-frequency bands of a picture; the image's important edges and characteristics are generally located in the same bands as the noise. Noise is commonly seen in the high-frequency bands of a picture. As a result, the fundamental challenge in the picture noise reduction procedure is to remove noise while still retaining the borders and other crucial image information. In recent years, a large number of noise-reduction strategies have been presented. This method based on fuzzy theory (Rajinikanth and Satapathy, 2018), is a good strategy.

### 3.4 Fuzzy C-mean (FCM) clustering algorithm and fuzzy features

Finite-state clustering using the FCM method enables a single piece of data to belong to two or more groups at the same time. Dunn (1973) created this approach, which was later refined by Bezdek (1981). FCM is a pattern recognition algorithm that is extensively utilised.

**Table 1** Wisconsin breast cancer data description of attributes

| *Attribute description* | *Value of attributes* | *Mean* | *Standard deviation* |
|---|---|---|---|
| Clump thickness | 0.1–1 | 0.442 | 0.282 |
| Uniformity of cell size | 0.1–1 | 0.313 | 0.305 |
| Uniformity of cell shape | 0.1–1 | 0.320 | 0.297 |
| Marginal adhesion | 0.1–1 | 0.280 | 0.286 |
| Single epithelial cell size | 0.1–1 | 0.321 | 0.221 |
| Bare nuclei | 0.1–1 | 0.346 | 0.364 |
| Bland chromatin | 0.1–1 | 0.343 | 0.244 |
| Normal nucleoli | 0.1–1 | 0.287 | 0.305 |
| Mitoses | 0.1–1 | 0.159 | 0.171 |

It is based on the minimisation of the objective function, which is detailed in further detail later. Table 1 shows the relationship between the equations below and the values in the table.

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{J} u_{ij}^m \left\| x_i - c_j \right\|^2, 1 \le m < \infty \tag{2}$$

The degree to which a $x_i$ belongs to the cluster is represented by the integer $u_{ij}$. $j$, $x_i$ represents the $i^{th}$ piece of $d$-dimensional measured data, $c_j$ represents the cluster's centre, and is any norm that indicates the similarity of any measured data to the centre.

## 3.5 Proposed breast cancer-classification

The HKH-ABO model, which is used in the classification layer of the BPBRW algorithmic framework, enhances classification accuracy. In addition, the HKH-ABO model is a hybrid of the Krill Herd optimisation (KHO) (Mohsenpourian et al., 2021) and African Buffalo optimisation (ABO) (Senthilkumar et al., 2022) models, with the KHO model acting as the foundation. Furthermore, hybridisation aims to increase the speed with which ailments are recognised and identified. It is initially built with the objective of categorising breast tumours using a dataset made up of neural network systems based on decision trees called the BPBRW model, which is employed to achieve this job. Group learning is a technique that may be used to a variety of problems, such as classification and regression. It is used to anticipate the result of a situation based on the training phase's building of decision trees and the testing phase's categorisation of unique trees. The filtered breast MRI dataset is divided into two groups, one for training samples and the other for testing samples. The testing samples are used specifically for the technique specified by equation (3).

$$D_s = \{(P_m, Q_m)\} m = 1, 2, ..., N \tag{3}$$

In this case, the breast MRI for 'm' numbers of patients is denoted as Pm ($p1_m...pM_m$) with $M$ characteristics, and the breast cancer tumour is denoted as $Q_m$, which contains information about the tumour such as whether it is benign or malignant.

When working with a large dataset with numerous variables, clustering the data is problematic since all of the variables cannot be reviewed at the same time. The process may thus also offer a particular possibility that a data point would fall into a certain set of data. LSTM (Antonini et al., 2015) is a kind of memory unit employed in this network that eliminates or inserts data in a meaningful way based on the cell state, which is controlled by structures known as gates. After a period of time, the degree of malignancy will vary depending on the severity of the infection. When it comes to cancer, the tumour's current size is determined by its previous characteristics. As a result, the prediction of tumour growth would be better if history were joined and developed at earlier time stages. Additionally, the LSTM arrangement provides a gating tool for acquiring data in order to avoid long-term dependency difficulties. This gating tool is comprised of an input gate, a hidden gate, and an output gate. As a result, Figure 3 depicts the whole procedure of the newly proposed approach.

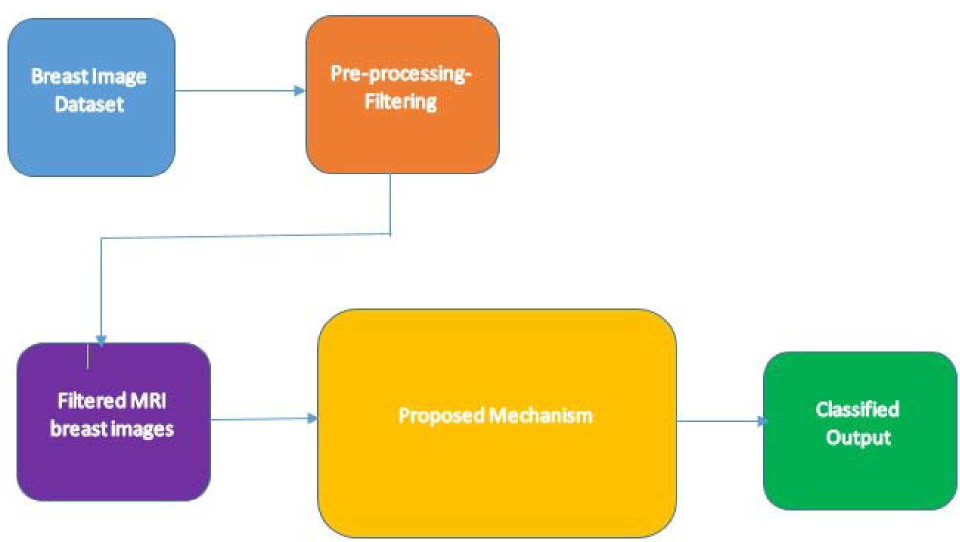
$$At = b + yht - 1 + xit \tag{4}$$

The BPBRW model is used to study the illnesses, and the filtered input photos are sent to it. The second portion is the output $ht$, the image feature is represented as $y$, and the prediction of illness characteristics from the training data is described in equation (5).

$$H_t = Q_m \left( P_m \right) \tag{5}$$

This function also identifies the sickness component, and the freshly generated HKH-ABO model is launched in this layer before being passed on to the output layer for processing. The krill herd's fitness remained unknown for a long time.

**Figure 3** Working process of the developed model (see online version for colours)

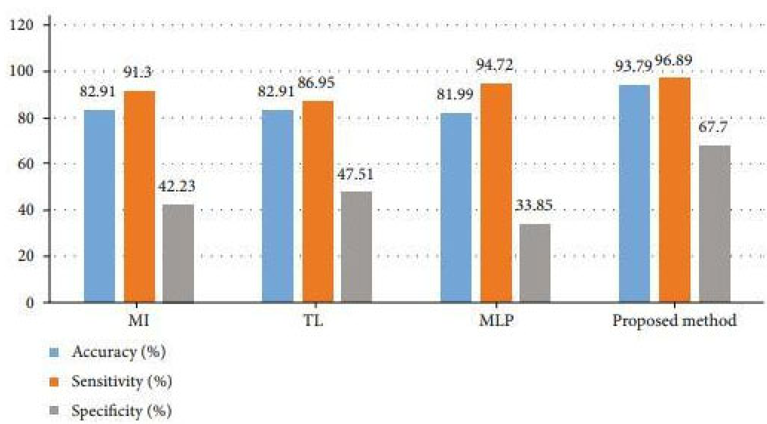


## 4 Result and discussion

In this article, the ultimate goal is to establish the clinical applicability of our unique SD-CNN technique for breast cancer detection in order to advance the field of research. As a result, we undertake two separate sets of experiments. This is the initial experiment, and its purpose is to verify the values derived from recombined photos in order to enhance breast cancer detection. Deep CNN and ResNet are used in this application. The second experiment will look at the possibilities of using SD-CNN to enhance the typical FFDM for the purpose of improving diagnostic accuracy. In this study, a publicly available FFDM dataset from the IN breast is utilised, and the findings are compared to those obtained by six cutting-edge algorithms.

They are fed into the ResNet, which has been taught to recognise them. We have all of the characteristics input into the GBT in order to discriminate between malignant and benign instances in this study since features from different layers of ResNet depict pictures of various sizes and viewpoints. The approaches are implemented via the usage of a Python package known as 'sklearn', which is responsible for their development. It is necessary to employ different parameters in order to avoid the model from overfitting. Consider the following illustration: By limiting the number of decision trees to 21, we apply an early halting strategy. For each split, the maximum number of features to be searched was set to N, while the minimum number of samples falling into each leaf node was set to 2. The procedure of validating the process on the basis of digital mammography pictures is shown in the graph in Figure 4.

**Figure 4** The comparison results (see online version for colours)




Thus, the newly developed BPBRW with HKH-ABO model has effectively predicted breast cancer at the beginning level, with outstanding accuracy, sensitivity, precision and specificity.

Evaluation of state-of-the-art methodologies, including recall, specificity, and decreased error rate, is shown here. By comparing all of the current models, the suggested model has sought to get superior outcomes in all dimensions.

## 5 Conclusions

When employed on mammograms, these CNNs are capable of distinguishing between normal and abnormal mammograms. An automated detection method for breast cancer was shown in the current research using a CAD system. Mammogram pictures were initially subjected to pre-processing techniques such as image contrast enhancement and noise reduction in order to improve and prepare them for the subsequent phases. After that, an image segmentation approach based on colour space was applied, which was then followed by mathematical morphology to create a final product. Finally, for feature classification, a new optimised version of the CNN and a new enhanced metaheuristic, referred to as the advanced thermal exchange optimisation method were used in conjunction with each other. Furthermore, refining the structure of the SVM and adding fuzzy features as inputs to the improved classifier results in a considerable improvement in the accuracy of the proposed system, which may reach up to 98.85% accuracy. The conclusion of the suggested model has shown that it is capable of efficiently detecting breast cancer in its early stages, whether it is of the benign or malignant kind. Our findings were also computed automatically without the need for picture pre-processing to get perspective sensitivity values, which reduced the possibility of human error and bias while increasing the effectiveness of the study. In the future, one of our goals will be to uncover probable clinical interpretations based on the traits. This will be one of our future efforts. Using the example above, as the ResNet is built up deeper, the initial layers of features may represent the raw imaging characteristics as represented by the first-order statistics, and the deeper layers of features may represent the morphological characteristics as represented by the second-order statistics (e.g., shape).

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