

DEVELOPING MULTI-LABEL BREAST CANCER SCREENING USING EFFICIENTNETB3 FEATURE EXTRACTOR

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ABSTRACT

Breast cancer is the first new case occurring and the fifth death-causing cancer disease in 2020, which collapses the families as women are the pillar of the family members. 3D image acquisition technology increases treatment methods and decreases the rate of breast cancer death. Furthermore, single-label breast cancer classifications are deployed to solve the problem. However, it cannot convey more information about mammogram images. In the area where the shortage of datasets is there as in the medical image, data augmentation and transfer learning are the best solution. A Multi-Label Breast Cancer Screening is a deep learning model using a transfer learning model that gives information on finding, density, and pathology of patients' breast mammograms to the radiologists, aiming for life-saving and supporting the family. The existing model shows low accuracy on feature extraction and more layers with a very large number of nodes in a layer in the classification part. In this study, the best feature extractor for this particular work is investigated and identified as efficientnetb3, and ONN is used for the classification part. The proposed model outperforms the previous work in all evaluation metrics with a 13.25% f1_score, 53% hamming loss, 36.7% coverage error, and 12.5 an exact match. And, the number of parameters were decreased from 134M to 20M which was resulted from the optimizing of classification part of the model. The developed model with ONN in the classification part has made the best improvement over the existing model in terms of evaluation metrics and network performances.

KEYWORDS

Breast Cancer, Efficientnetb3, Screening, Mammogram, Transfer Learning, Multilabel

1. INTRODUCTION

Cancer is a large group of diseases characterized by cells that grow uncontrollably, invade the nearest organ, and/or spread beyond their usual limits. It can begin in any organ or tissue in the body. A malignant tumor is another common name for cancer. Breast, lung, colorectal, prostate, and stomach are the top-5 organ affected by cancer diseases (Sung et al., 2021).

Throughout the world, 19.3 million new cancer cases are assessed and nearly 10.0 million cancer deaths took place in 2020. Breast cancer in women has replaced lung cancer as new cases analyzed cancer from the top-5 lung, colon, prostate, and stomach cancers (Sung et al., 2021). Lung cancer stayed the highest cause of cancer deaths from colon, liver, stomach, and female breast cancers, and the percentage is given in figure 1.1 graphically. Death rates have reduced since 1989 and these decreases are assumed to be the outcome of treatment advances, earlier detection by screening, and enhanced awareness. Early detection of breast cancer is to be the best way to save lives and decrease healthcare costs over time (Siegel et al., 2017). Figure 1.1 shows this graphically.

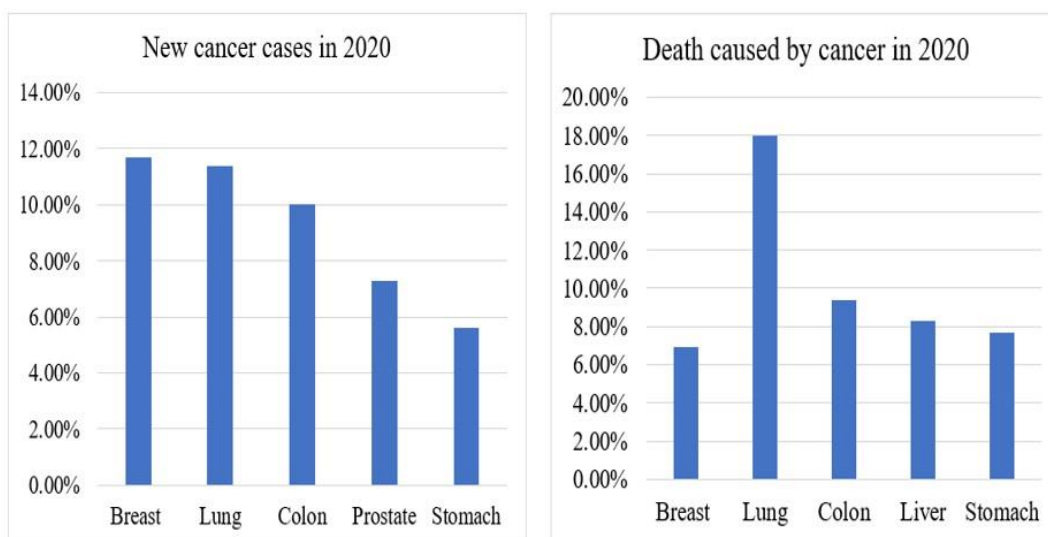


Figure 1. Cancer new cases and death rates per top-5 organs

Image acquisition and interpreting technologies to detect and diagnose breast cancer continue to advance aiming to give a better diagnosis and less dangerous option for patients (Narod et al., 2015). Mammography¹ is the major cause of breast cancer mortality reduction, although there is a potential limitation to the procedure (Heywang-Köbrunner et al., 2011). In fact, reading a mammogram correctly is challenging for most radiologists. In a survey (Whang et al., 2013), error in diagnosis was the major cause of misconduct accommodate against radiologists. Many of such cases started from the image quality or the radiologist's unsuccess to diagnose breast cancer on mammograms (Whang et al., 2013). To increase the rate of accurate diagnoses, lesions that contain a 2% probability of being malignant are advocated for a biopsy (Sickles, n.d.). However, malignant biopsies detected are only 15 to 30% (Sickles, n.d.). Pain, fear, anxiety, direct financial losses, indirect costs lost for work lost, and complexity risks are the risks caused by benign biopsies (Review et al., 2006).

Most of the available works depend on single-label screening, in which every mammogram is thought to contain only one label from the given mammogram characteristics. Moreover, the study (Jiao et al., 2016) focused on the masses in a mammogram to diagnosis patients. In other studies (Karahaliou et al., 2008; Wang et al., 2016), researchers used micro-calcification to screen breast cancer. While authors (Arevalo et al., 2016; Berment et al., 2014; Chougrad et al., 2018; Jiang et al., 2014; Jiao et al., 2016; H. Li et al., 2017) depended on the morphology of the form and shape of the breast mass injury in mammograms pictures, expecting it is the foremost contrasting criteria among kind and harmful masses. Other works in (Gastouniotti et al., 2016; Vachon et al., 2007; Winkel et al., 2016) researchers depended on the mammographic density and parenchyma patterns for breast cancer risk measurement.

These methods, although working well, it has difficult to raise the relationship that exists among the different annotations to help to give a full diagnosis. Single-label screening is the foundation for multi-label screening which aims to forecast the set of important labels for a given input. The inputs utilized to to prepare such a demonstrate for this sort of issue have a few names. The multi-class and multi-label classification differ in terms of output label space. labels are not thought to be mutually exclusive in multi-class whereas it is independent in multi-label. (Madjarov et al., 2012; Zhang & Zhou, 2014).

In this, works efficientnetb3 as feature extraction will be used along with less layered and small nodes in a fully connected neural network. This will be done by empirical selection of transferable model from Keras application on a fully annotated dataset for Multi-Label Breast Cancer Screening (ML-BCS).

2. RELATED WORKS

The researchers, in (H. Li et al., 2017) come up with new techniques to convert the 2D contour of breast mass in mammography to a 1D signature. The techniques can express the contour features as well as the regularity of breast mass. Four local features within the new contour descriptor are extracted from subsections. RMS slope describes the new contour. KNN, SVM, and ANN classifiers are used to identify benign breast mass and malignant mass. However, the study was based on ML and a single-label classification problem.

In (Chougrad et al., 2018) works three most impressive CNN architectures proposed at that time: VGG16, ResNet50, and Inception v3 (Sangeetha & Prasad, 2006; Simonyan & Zisserman, 2015; Szegedy et al., 2016) trained on ImageNet (Fei-Fei et al., 2010) was used. The study investigates the benefit of transfer learning rather than random initialization for every model and finds effective fine-tuning methods. The primary aim of that work is to develop state-of-the-art CNNs and to use transfer learning, to build a powerful mass lesion screening tool that can help the radiologist get support to give more accurate diagnoses. Again, the research is a single-label classification problem.

Other researchers (Nawaz et al., 2018), develop a DL method based on a CNN model classification for multi-class breast cancer. The objective of the proposed approach is to distinguish the breast tumors as kind or harmful but the study predicts the subclass of the tumors as Fibroadenoma, Lobular carcinoma, etc. The work results on histopathological images on the Break his dataset and showed that the Dense Net CNN model attained high processing efficiencies in the multi-class screening of breast cancer tasks when compared with state-of-the-art models. However, the study was not considered the multi-label transformation or algorithm adoption problem.

The work proposes an "end-to-end" approach (Shen, 2017) in which a fully annotated data set with ROI information is used and a model identifies local image patches using pre-trained models. In this study, lesion annotations are expected only in the first phase of training and succeeding stages expect limited to image-level labels, solving the reliance on hardly available lesion annotations.

But this study worked on how to annotate the breast cancer lesion automatically by deep learning. The CNN methods VGG16 and ResNet50 are used to classify mammograms to get good performance compared to the model before them.

Furthermore study (Chougrad et al., 2020), proposes the joint learning of the tasks using multilabel image classification. Also, analysts present a diverse fine-tuning strategy to apply a pre-trained demonstrate, that takes benefits of the complete picture representation learning whereas adjusting the pre-trained weight to the errand. so, they propose a customized name choice plot, adjusted to the multi-label interpretation issue, which estimates the ideal believe for each visual concept. But this study was used the label powerset which was computationally expensive to transform the multi-label classification to single-label classification and correlated each label.

A novel classification approach DeepBC for identifying the breast mammogram pathology, depending on the deep CNNs is proposed by (Wenzhong et al., 2020). DeepBC is the sequential

integration of Inception, ResNet, and AlexNet to extract features from mammograms and classifies mammograms as malignant or benign tissues. DeepBC model is intended and proposed to reliably and accurately solve the classification of breast cancer. However, this study has low accuracy and is inefficient in terms of time and computation.

3. MATERIAL AND METHODS

To design or develop Multi-Label Breast Cancer Screening we used transfer learning feature extractor with fully connected neural networks. Medical image has specific standard file extension to store, compress, retrieve and put as a dataset and make it available online. This file extension is .dcm and is known as Digital Image Communication in Medicine. This is what makes the medical image dataset more difficult to use directly in the CNN model. Before using such a dataset, it must be converted to JPG/PNG file format. Then we applied Preprocessing. Finally, we started applying fully connected NN. Figure 2 explains the process flow of the proposed solution.

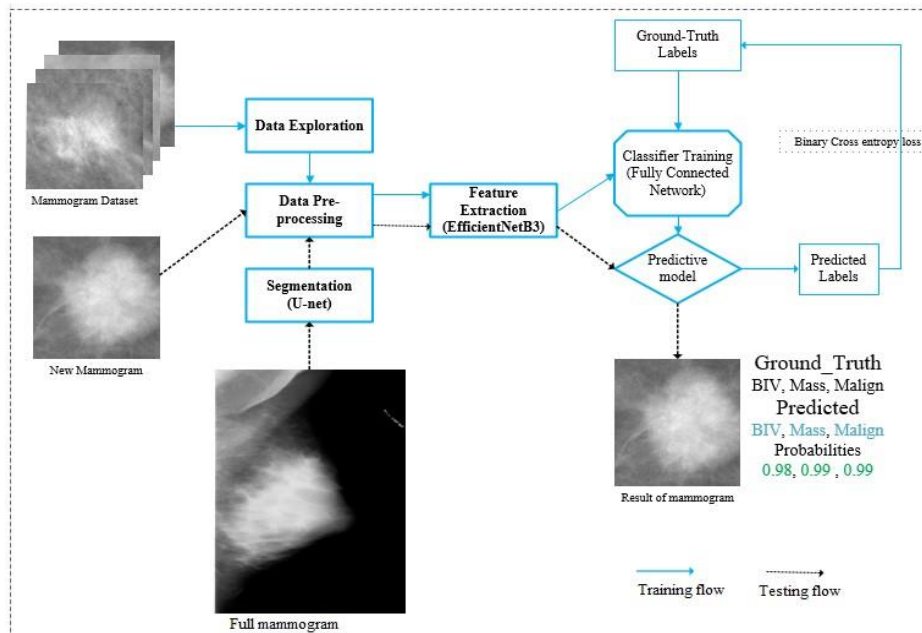


Figure 2. process flow of the proposed solution

3.1. Dataset Preparation

In our study we target to medical images. It has specific standard file extension to store, compress, retrieve and put as a dataset and make it available online. This file extension is .dcm and is known as Digital Image Communication in Medicine. This is what makes the medical image dataset more difficult to use directly in the CNN model. Before using such a dataset, it must be converted to JPG/PNG file format. This data set is publicly available on the website at: <https://wiki.cancerimagingarchive.net/display/Public/CBIS-DDSM>² and when downloaded on a local hard disk its size is 152GB. It has full mammogram images, cropped images, masks, and labels description of an image in excel .csv file format. Each image file in this dataset is separated by an individual folder and it is merged with many folders.

3.2. Model Implementation

We used Python 3.9 to implement experiments. We used all Keras applications that are DL models which are supplied with pre-trained weights. After the empirical experiments, four models were implemented and the details are given below.

A. *EfficientNetB4 Implementation*

The efficientNetB4 model seems to have good f1_score accuracy. However, it needs a large amount of dataset unfortunately it's affected with high overfitting with a small dataset. Its snip code is given below:

```
# Transfer learning model -EfficientNetB4
def effnetb4_model():
    effnetb4 = EfficientNetB4(include_top=False,
        weights="imagenet", input_shape=INPUT_SHAPE)
    model = Sequential([
        base_model_efficientnet,
        Flatten(),
        Dense(128, activation='relu'),
        Dropout(0.2),
        Dense(8, activation='sigmoid')
    ])
    return model
model = effnetb4_model()
```

Snip Code 1. Efficientnetb4 snip code

B. *VGG16 Implementation*

VGG16 is the baseline paper model and it follows the procedure explained in that paper. The feature extraction part and classification part are implemented as original papers(Simonyan & Zisserman, 2015) except for output layers. 15 epochs were trained using imagenet weight to initialize the kernel with Adam optimizer. Again, 90 epochs were trained by using weight trained on the first 15 epochs and SGD optimizer used. Its snip code is given below.

```
def vgg16_model():
    base_model_vgg = VGG16(include_top=False,
        weights="imagenet", input_tensor=None, input_shape=(224,
        224, 3))
    model = Sequential([
        base_model_vgg,
        Flatten(),
        Dense(4096, activation='relu'),
        Dropout(0.2),
        Dense(4096, activation='relu'),
        Dropout(0.2),
        Dense(8, activation='sigmoid')
    ])
    return model
model = vgg16_model()
```

Snip Code 2. VGG snip code

C. DensenetNet121 Implementation

Densenet121 is the second better result-producing model among deep learning models available on keras application for this specific work. The snip code for densenet121 is given as follows.

```
# Transfer learning model -DenseNet121
def dnet121_model():
    dnet121 = DenseNet121(weights='imagenet',
include_top=False, input_shape = INPUT_SHAPE)
    model = Sequential([
        dnet121,
        Flatten(),
        Dense(128, activation='relu'),
        Dropout(0.2),
        Dense(8, activation='sigmoid')
    ])
    return model
model = dnet121_model()
```

Snip Code 3. Densenet121 snip code

D. EfficientNetB3 + ONN implementation

EfficientNetB3 is the model that gives the best result in this works. Its snip code showing transferable form is given below.

```
# Transfer learning model - EfficientNetB3
def effnetb3_model():
    effnetb3 = EfficientNetB3(include_top=False,
weights="imagenet", input_shape=(224, 224, 3))
    model = Sequential([
        effnetb3,
        Flatten(),
        Dense(128, activation='relu'),
        Dropout(0.2),
        Dense(8, activation='sigmoid')
    ])
    return model
model = effnetb3_model()
```

Snip Code 4. Efficientnetb3 snip code

4. RESULTS AND DISCUSSIONS

We connected MLP in order to classify the cancer scerring. We ran numerous tests to assess the comes about based on tuning parameters for MLP. Firstly, we settled the number of ages and changed the number of neurons at each covered up layer. The created MLP comprises of two covered up layers, we begun with 32 neurons for each layer, and after that we attempted diverse numbers of neurons (64,128, and 265). Too, we ran the explore with a diverse number of neurons per covered up layer we set the number of neurons as 64 within the to begin with layer and 32 within the moment layer. We rehashed each try 5 times and took the average of the exactness

comes about. Too, we utilized portion of dataset for assessment. The assessment information set isn't utilized for preparing to calculate exact result without overfitting for preparing information. Table (2) appears the precision comes about with diverse number of neurons for covered up layers.

EfficientNetB4 shows high accuracy on the training set. However, on testing set and evaluation metrics, it has the least value. The regularization method is used for reducing overfitting and it is experimentally identified as a problem of the small dataset used. This is due to the high parameters it calculates on a small number of data and overfitting is occurred. On the other hand, VGG16 has the lowest training accuracy. But on evaluation metrics, its values are greater than that of efficientnetb4. Densenet121 has the lowest computational cost and training time. But its precision is littler than that of efficientnetb3.

Efficientnetb3 is explored and recognized as the leading include extractor by replying the primary investigate address to be replied by this works. Among the conducted experiments efficientnetb3 model gave the best performance results. The model outperforms the previous work (vgg16 model) in all evaluation metrics. 13.25% in f1-score, 53% in hamming loss, 36.7% in coverage error, and 12.35% in an exact match are percentages improved over baseline paper by this works. This guarantees that efficientnetb3 is the best feature extractor for multi-label classification. The results demonstrate that the proposed show accomplishes a considerable enhancement over existing strategies in terms of all conducted assessment measurements.

In addition, vgg16 has 7 x 7 x 512 shape extracted features followed by 3 layers with 4096, 4096, 8 nodes. The maximum number of nodes found fully connected layer increases the computation cost of the model. 134M parameters are calculated which affect the model performance. To reduce this computational fetched and increment precision completely associated NN with few layers and a little number of hubs are utilized. Accordingly, 2 layers with 128 and 8 nodes are optimized for this works. The classification portion of the show is decreased and the number of parameters diminished to 20M. This optimization answers the second research question of this work by reducing the parameter in baseline work by 114M. Except for vgg16, all three models have the same classification part. However, the difference in fully connected NN parameters comes from the flatten function of each model. They have different feature maps which affect the number of parameters. Table 1 compares the evaluation metrics of 4 models on the same datasets. Efficientnet3 shows the best experimental results on all the evaluation metrics

Table 1. The result of evaluation metrics with different models

Models	Evaluation Metrics			
	F1-Score	Hamming_Loss	Coverage error	Exact Match
Efficientnetb4	0.66±0.025	0.27±0.026	6.72±0.015	0.575±0.015
VGG16	0.83±0.017	0.132±0.015	5.88±0.015	0.71±0.015
Densenet121	0.91±0.015	0.091±0.017	5.01±0.029	0.76±0.057
Efficientnetb3 + ONN (proposed)	0.94±0.007	0.044±0.0025	3.72±0.015	0.81±0.0025

The result values that increment or decrement in small numbers come from 5-fold cross-validation applied during training. Figure 3 shows the accuracy and loss graph of 5-fold results for efficientnetb3.

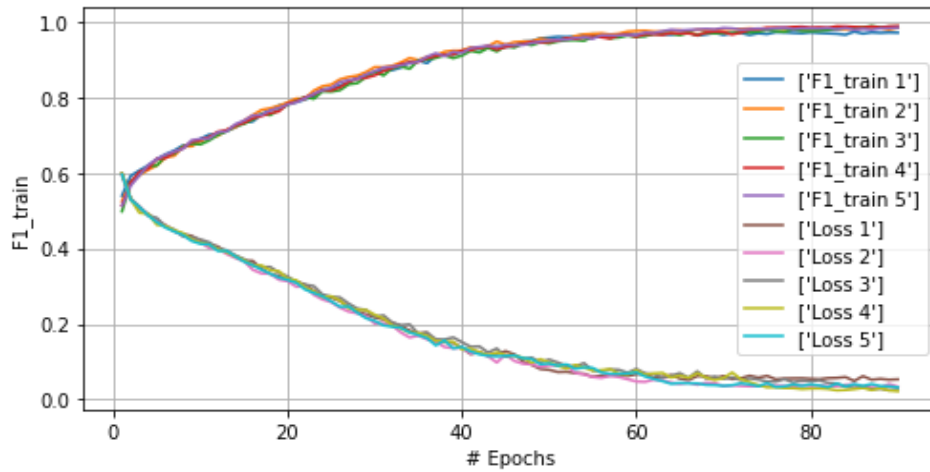


Figure 3. Accuracy and loss of 5-fold cross-validation

Figure 4 shows the comparison of four models' accuracy and loss in a graph. The difference between the model is visible. Efficientnetb3 has the most elevated precision and the most reduced misfortune in preparing. Again, it has the highest accuracy in validation accuracy and nearly lower value in validation loss.

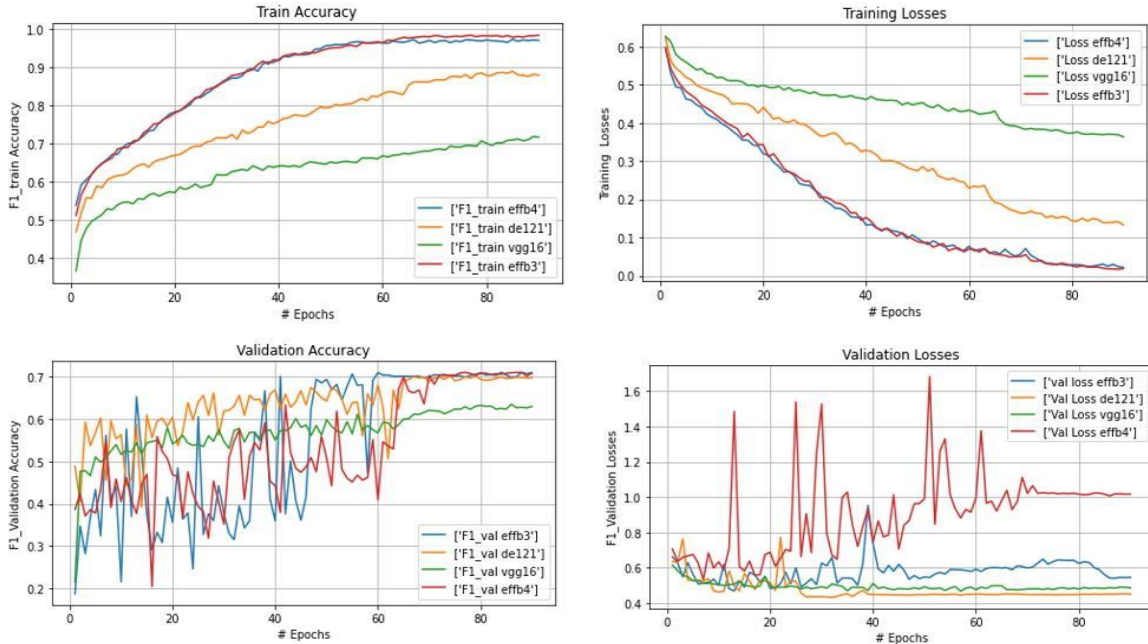


Figure 4. Accuracy and losses comparison of the models

Different experiments are conducted to optimize the neural network in the classification parts of the model. At first, the efficientnetb3 with 8 output layers is implemented. The result is good but needs to optimize more. Second, it is implemented with 64 in hidden layers and 8 in output layers

are implemented. Next, 128 hidden layers with 8 output layers are implemented with efficientnetb3 resulting in an optimized solution compared to other results. It is practically optimal since the results of NN with greater values and smaller values are less than the result of 128 and 8 nodes. Finally, the value of 256 nodes in a first layer, 128 layers in hidden layers, and 8 nodes in the last layer result in nearly fewer values compared to the optimal values.

Table 2. Results of efficientnetb3 within the models

Models	Evaluation Metrics			
	F1-Score	Hamming_Loss	Coverage error	Exact Match
Efficientnetb3 + 8	0.92±0.01	0.046±0.015	3.81±0.012	0.79±0.01
Efficientnetb3 + 64+8	0.92±0.009	0.045±0.006	3.73±0.034	0.80±0.02
Efficientnetb3 +256 + 128+8	0.94±0.002	0.044±0.015	3.72±0.024	0.80±0.01
Efficientnetb3+128 + 8	0.94±0.005	0.044±0.0017	3.72±0.025	0.81±0.0026

5. CONCLUSION

Cancer is a disease caused by uncontrolled cell replication and breast cancer is one type that originated in the breast. Breast cancer cells more often than not shape tumors, which can as a rule be seen on Xrays. It happens generally in ladies, and some of the time men too create breast cancer. The root of breast cancer is the tube that carries drain to the areola. Now and then it starts within the organs that make breast drain.

Single label classification with one particular category was done already. Some use mass finding while other use calcification. Thickness is additionally utilized by other considers to screen breast cancer. But mammogram gives more names or data at the same time. Multi-label classification handles this issue by giving numerous prescient reports at the same time.

Efficientnetb4 shows good accuracy during training. Unfortunately, it has the least evaluation metrics compared to other conducted experiments. This comes from a high number of parameters it computes on a small dataset. Vgg16 has the least accuracy graph but in evaluation metrics, its values are greater than efficientnetb4 values. In addition, densenet121 is optimal in computational cost and training time.

The empirical study conducted specify that efficientnetb3 was investigated as the best feature extractor for this works from the pre-trained Keras application. The demonstrate comes about appear that it has the most noteworthy values in all assessment measurements. Once more, it is proficient in terms of preparing time and computational taken a toll. Furthermore, a fully connected neural network that has 2 layers excluding the input layer from the feature vector and 128 and 8 nodes optimize the numbers of parameters dramatically from 134M to 20M compared to vgg16. The model is multi-label classification and reports three subcategories for one image at the same time.

The results have shown that the efficientnetb3 model has outperformed all conducted experiments. It made more improvement on the baseline paper. 13.25% in f1-score, 53% in hamming loss, 36.7% in coverage error, and 12.35% in an exact match are percentages of improvement on evaluation metrics when compared with the previous works. Densenet121 has

shown better performance next to the efficientnetb3 in evaluation metrics and has the best computational cost and training time.

In conclusion, an efficientnetb3 feature extractor with ONN confirms the best improvement on all evaluation metrics and reduces the computational cost and training time effectively.

6. FUTURE WORKS

Optimizing feature extractor by cutting in numerous layers with consistent completely associated NN assist is prescribed since this increments the precision and diminishes parameters to be calculated.

In addition, the dataset contains imbalanced numbers in the density subcategory. Depending on this imbalance data the validation accuracy and validation loss of the model are low and there is some incorrect classification. It is the recommendation of this works to use the customized loss function which is the dataset-specific loss function to solve this problem. Besides, using more mammogram datasets and other modalities of breast datasets is extend this work in the future.

REFERENCES

- [1] Allaouzi, I., & Ben Ahmed, M. (2019). A Novel Approach for Multi-Label Chest X-Ray Classification of Common Thorax Diseases. *IEEE Access*, 7, 64279–64288.
- [2] Basha, S. H. S., Dubey, S. R., Pulabaigari, V., & Mukherjee, S. (2020). Impact of fully connected layers on performance of convolutional neural networks for image classification. *Neurocomputing*, 378, 112–
- [3] Chougrad, H., Zouaki, H., & Alheyane, O. (2018). Deep Convolutional Neural Networks for breast cancer screening. *Computer Methods and Programs in Biomedicine*, 157, 19–30.
- [4] Chougrad, H., Zouaki, H., & Alheyane, O. (2020). Multi-label transfer learning for the early diagnosis of breast cancer. *Neurocomputing*, 392(February), 168–180.
- [5] Diagnosis, S. V. (2005). *Benefits and Limitations of Mammography*. Dc, 1–18.
- [6] Fei-Fei, L., Deng, J., & Li, K. (2010). ImageNet: Constructing a large-scale image database. *Journal of Vision*, 9(8), 1037–1037.
- [7] Gastouniotti, A., Conant, E. F., & Kontos, D. (2016). Beyond breast density: A review on the advancing role of parenchymal texture analysis in breast cancer risk assessment. *Breast Cancer Research*, 18(1), 1–12.
- [8] Heywang-Köbrunner, S. H., Hacker, A., & Sedlacek, S. (2011). Advantages and disadvantages of mammography screening. *Breast Care*, 6(3), 199–207.
- [9] Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, 2017-Janua*, 2261–2269.
- [10] Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, 2017-Janua*, 2261–2269.
- [11] Jiang, M., Zhang, S., Liu, J., Shen, T., & Metaxas, D. N. (2014). Computer-aided diagnosis of mammographic masses using vocabulary tree-based image retrieval. *2014 IEEE 11th International Symposium on Biomedical Imaging, ISBI 2014*, 1123–1126.
- [12] Jiao, Z., Gao, X., Wang, Y., & Li, J. (2016). A deep feature based framework for breast masses classification. *Neurocomputing*, 197, 221–231.
- [13] Karahaliou, A. N., Boniatis, I. S., Skiadopoulos, S. G., Sakellaropoulos, F. N., Arikidis, N. S., Likaki, L. E. A., Panayiotakis, G. S., & Costaridou, L. I. (2008). Breast cancer diagnosis: Analyzing texture of tissue surrounding microcalcifications. *IEEE Transactions on Information Technology in Biomedicine*, 12(6), 731–738.
- [14] Kim, M., Yun, J., Cho, Y., Shin, K., Jang, R., Bae, H. J., & Kim, N. (2019). Deep learning in medical imaging. *Neurospine*, 16(4), 657–668.

- [15] Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>.
- [16] Lee, R. S., Gimenez, F., Hoogi, A., Miyake, K. K., Gorovoy, M., & Rubin, D. L. (2017). Data Descriptor: A curated mammography data set for use in computer-aided detection and diagnosis research. *Scientific Data*, 4, 1–9.
- [17] Li, H., Meng, X., Wang, T., Tang, Y., & Yin, Y. (2017). Breast masses in mammography classification with local contour features. *BioMedical Engineering Online*, 16(1), 1–12.
- [18] SLi, M., & Zhou, Z. H. (2007). Improve computer-aided diagnosis with machine learning techniques using undiagnosed samples. *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans*, 37(6), 1088–1098.
- [19] Madjarov, G., Kocev, D., Gjorgjevikj, D., & Džeroski, S. (2012). An extensive experimental comparison of methods for multi-label learning. *Pattern Recognition*, 45(9), 3084–3104.
- [20] Narod, S. A., Iqbal, J., & Miller, A. B. (2015). Why have breast cancer mortality rates declined? *Journal of Cancer Policy*, 5, 8–17. <https://doi.org/10.1016/j.jcipo.2015.03.002>
- [21] Navab, N., Hornegger, J., Wells, W. M., & Frangi, A. F. (2015). Medical Image Computing and Computer-Assisted Intervention - MICCAI 2015: 18th International Conference Munich,
- [22] Nawaz, M., Sewissy, A. A., & Soliman, T. H. A. (2018). Multi-class breast cancer classification using deep learning convolutional neural network. *International Journal of Advanced Computer Science and Applications*, 9(6), 316–322.
- [23] Review, N., Diabetes, K. T., Umpierrez, G. E., Smiley, D., & Kitabchi, A. E. (2006). *Annals of Internal Medicine Review*. 350–358.
- [24] Ritter, F., Boskamp, T., Homeyer, A., Laue, H., Schwier, M., Link, F., & Peitgen, H.-O. (2011). Medical Image Analysis: A Visual Approach. *IEEE Pulse*, 2(6), 60–70.
- [25] Sangeetha, V., & Prasad, K. J. R. (2006). Syntheses of novel derivatives of 2-acetylfuro [2,3a] carbazoles, benzo [1,2-b]-1,4-thiazepino[2,3-a]carbazoles and 1-acetyloxycarbazole-2-carbaldehydes. *Indian Journal of Chemistry - Section B Organic and Medicinal Chemistry*, 45(8), 1951–1954. <https://doi.org/10.1002/chin.200650130>
- [26] Shen, L. (2017). End-to-end training for whole image breast cancer diagnosis using an all convolutional design. *ArXiv*, August, 1–12. <https://doi.org/10.1038/s41598-019-48995-4>
- [27] Shiraishi, J., Li, Q., Appelbaum, D., & Doi, K. (2011). Computer-aided diagnosis and artificial intelligence in clinical imaging. *Seminars in Nuclear Medicine*, 41(6), 449–462. <https://doi.org/10.1053/j.semnuclmed.2011.06.004>
- [28] Sickles, a. (n.d.). *Breast Periodic Benign Lesions : Results*. 463–468.
- [29] Siegel, R. L., Miller, K. D., & Jemal, A. (2017). Cancer statistics, 2017. *CA: A Cancer Journal for Clinicians*, 67(1), 7–30. <https://doi.org/10.3322/caac.21387>
- [30] Simonyan, K., & Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition. *3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings*, 1–14.
- [31] Stoitsis, J., Valavanis, I., Mouggiakakou, S. G., Golemati, S., Nikita, A., & Nikita, K. S. (2006). Computer aided diagnosis based on medical image processing and artificial intelligence methods. *Nuclear Instruments and Methods in Physics Research, Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, 569(2 SPEC. ISS.), 591–595.
- [32] Sung, H., Ferlay, J., Siegel, R. L., Laversanne, M., Soerjomataram, I., Jemal, A., & Bray, F. (2021). Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *CA: A Cancer Journal for Clinicians*, 0(0), 1– 41. <https://doi.org/10.3322/caac.21660>
- [33] Suzuki, K. (2013). Machine learning in computer-aided diagnosis of the thorax and colon in CT: A survey. *IEICE Transactions on Information and Systems*, E96-D(4), 772–783. <https://doi.org/10.1587/transinf.E96.D.772>
- [34] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the Inception Architecture for Computer Vision. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2016-Decem*, 2818–2826.
- [35] Vachon, C. M., van Gils, C. H., Sellers, T. A., Ghosh, K., Pruthi, S., Brandt, K. R., & Pankratz, V. S. (2007). Mammographic density, breast cancer risk and risk prediction. *Breast Cancer Research*, 9(6). <https://doi.org/10.1186/bcr1829>

- [36] Wang, J., Yang, X., Cai, H., Tan, W., Jin, C., & Li, L. (2016). Discrimination of Breast Cancer with Microcalcifications on Mammography by Deep Learning. *Scientific Reports*, 6(June), 1–9. <https://doi.org/10.1038/srep27327>
- [37] Wenzhong, L., Huanlan, L., Caijian, H., &Liangjun, Z. (2020). *Classifications of Breast Cancer Images by Deep Learning*. <https://doi.org/10.1101/2020.06.13.20130633>
- [38] Whang, J. S., Baker, S. R., Patel, R., Luk, L., & Castro, A. (2013). The causes of medical malpractice suits against radiologists in the United States. *Radiology*, 266(2), 548–554. <https://doi.org/10.1148/radiol.12111119>
- [39] Winkel, R. R., von Euler-Chelpin, M., Nielsen, M., Petersen, K., Lillholm, M., Nielsen, M. B., Lynge, E., Uldall, W. Y., & Vejborg, I. (2016). Mammographic density and structural features can individually and jointly contribute to breast cancer risk assessment in mammography screening: A case-control study. *BMC Cancer*, 16(1), 1–12. <https://doi.org/10.1186/s12885-016-2450-7>
- [40] Zhang, M. L., & Zhou, Z. H. (2014). A review on multi-label learning algorithms. *IEEE Transactions on Knowledge and Data Engineering*, 26(8), 1819–1837. <https://doi.org/10.1109/TKDE.2013.39>