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Article

A Dual Approach for Optimizing Breast Cancer Mammogram Classification using ResNet50, SMOTE, CNN and LSTM

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Abstract: —Breast Cancer is one of the major health concern in the world where this disease can kill large number of women globally. This health concern is caused by the growth of abnormal tissue in the breast. The early detection is very crucial to prevent it from growing into a last stage, to detect this in early stages we need models that are able to detect the disease efficiently. Deep learning algorithms are shown effective results in predicting the diseases, the imbalanced datasets in medical diagnosis helps in developing classification models that gives accurate results. Some of the existing models were providing some moderate accuracy results and to improve that accuracy more we are proposing a stacked model that uses balanced and imbalanced data.To handle this imbalanced data we are using a technique called (SMOTE) Synthetic Minority Over-sampling Technique, along with that we are using VGG16 preprocessing for input standardization and ResNet50 for feature exraction,and here in our proposed stacked model we are using CNN with multiple dense layers, although this CNN is best known for optimizing spatial features, it lacks in processing the temporal features that changes time to time so, to overcome this drawback here we are introducing the CNN along with LSTM here both the CNN and LSTM helps in optimizing the temporal features and spatial features that helps the trained model to predict the results correctly. This stacked method approach significantly improved the prediction results giving the accuracy of99.66% along with the other metrics like precision, recall, and F1score are giving 99.65%, 99.66%, 99.65% respectively.
Keywords: C SMOTE, VGG16, CNN, LSTM, ResNet50, feature extraction, breast tissue, balanced dataset, imbalanced dataset.

1. INTRODUCTION

Breast Cancer is considered to be one of the fastest growing disease and this rapid growth of the breast cancer is causing most of the cancer relateddeaths among women in the world, these deaths are affecting millions of people every year [1]. since 1989 we havedeveloped advanced treatments, increased awareness, and effective screening methods to reduce death rates [3], even though we have all of that,still breast cancer iscontinuouslyrising, from 2012 to 2020 we can see the increasing cases that went from 1.6 million to 2.2 million [2], [4]. By the year of 2025 the case rates are increased from 2.2 million to 19.3 million, this report was provided by (WHO) World Health Organization [6]. And when we look at the survival rates the countries with high income are having higher survival rates like for example japan is having the survival rate around 60% and we can see the same survival rate with the Sweden, in north America we can see the survival rate up to 80% whereas the countries with low income are having the survival rate up to 40%, this is due tolack of early-detection programs and healthcare facilities.Early detection of breast cancer is very important, because it will decrease the death rates by detecting early and provides appropriate diagnosis, while improving the survival rates[5]. Previously the breast cancer detection is done manually where we require skilled professionals, these experts detect the disease by looking at the scans like biopsy [8], Mammography,MRI,and ultrasound. However, this manual process of experts detecting may lead to false results because sometimes they might miss some details in the scanning images. Even sometimes the Mammography gives false results, especially in women whose breast carries dense tissues that are hard to analyze, this leads to unnecessary diagnosis for patients [10]. A biopsy can be applicable but there is a risk of infection and it might cause bruises [12].

If we use the ultrasound for detecting the BC it is not effective as it fails in providing the accuracy because sometimes it becomes operator-dependent[13]. And when we go with the MRI it is more expensive, and not available everywhere, and this also fails in predicting as its accuracy is not that great, moreover it results in unnecessary tests and anxiety [11]. Moreover, medical experts facedifferentobstacles and challenges indiagnosingbreast cancer accurately, including variability in interpretation, high workload, and the complexity of medical images. We are facing this challenge because of the shortage of experts, Therefore, the early detection and prevention of BC is necessary.

With the rapid development of technology, the ML and DL methods are providing greater results in BC detection and prediction [15]. However, in ML methods we needto extract the features manually, this manual feature extraction need medical expertise which can get complicated sometimes. Whereas theDL models can automatically extract the features from the dataset. with the help of these DL models the Feature extraction and data processing is simplified [21].The DL methodologies like CNNs which is known for convolutional neural networks is widely used in different areas of computer vision[22].The CNN was used many areas like feature extraction, medical image processing, image segmentation, and object detection. The CNN containsmultiple layers where these layers helps the model to identify significant features from the input data. Even though these CNN model are effective, they need larger datasets for training, this has become an issue for the medical field because of the limited data. here we are using CNN with LSTM and SMOTE to handle imbalanced data and VGG16 for feature extraction, the newly developed stacked modelis givingthe greater performance.

2. RELATED WORK

Breast cancer is one of the most raising cancer in the world and each year this cancer is affecting millions of women. From the last few years, researchers are working on different CNN models in order to detect the breast cancer. But still there is a lack of standard models thatdetermined as the best model this is because of thelack of large datasets where thesedatasets help inmodel training and testing. Hence, all the researchers now-a-days are focusing on using pre-trained models as feature extractors which are trained by feeding millions of images. With this motivation, m. masud et al., (2020) [1] introduced a paper that considers eight different pre-trained models where these models observe how the classification of breast cancers applying on ultrasound images. they also proposed a shallow CNN networkwhich outperforms the pre-trained models with all the performance metrics. their proposed model gave the accuracy of 100% and achieved 1.0 AUC score, whereas the best pre-trained model gives the accuracy of 92% and 0.972 AUC score. The model is trained using a fivefold cross validation technique,to avoid biasness. Moreover, the model is faster in training than the pre-trained models and requires a small number of trainable parameters.

Lindsey et al., (2015) [2] did a study on global cancer statistics, Cancer is a burden on society in economically developed countries and developing countries. Because of the growth and aging of the population the the occurrence of cancer is increasing, not only because of the growth of the population this breast cancer is increasing because of the other factors such as smoking, overweight, physical inactivity, and changing reproductive patterns.14.1 million new cancer cases are occurred in 2012 and up to 8.2 million deaths occurred in 2012 worldwide. Over the years, according to GLOBOCAN estimates the burden was shifted to less developed countries, which currently account for about 57% of cases and 65% of cancer deaths worldwide. Even thoughthe incidence rates for all cancers by combining are nearly twice as high in more developed countries when compared with the less developed countries in both males & females, this reflects the differences in the types of cancers, these are affected by detection practices, and the availability of treatment. Some factors come with the leading causes of cancer death like tobacco use, overweight or obesity & physical inactivity and infection. Some of the cancer cases are prevented by applying effective prevention measures, likecontrolling tobacco consumption, vaccination, and the use of early detection tests.

Gradishar et al., (2022) [5] described The therapeutic options for patients with non-invasive or invasive breast cancer are complex and varied. These NCCN Clinical Practice Guidelines for Breast Cancer include recommendations for clinical management of patients with carcinoma in situ, invasive breast cancer, Paget disease, phyllodes tumor, inflammatory breast cancer, and management of breast cancer during pregnancy. The content featured in this issue focuses on the recommendations for overall management of ductal carcinoma in situ and the workup and locoregional management of early stage invasive breast cancer. For the full version of the NCCN Guidelines for Breast Cancer, visit NCCN.org.

To detect the breast cancer in women mammography is widely used but the mammography does not show effective results for women who have dense breast. So E.D. Pisano et al., (2005) [7] gave a study to find out whether we can avoid some of the limitations of mammography. Here in this study they have presented a total number of 49,528 women for screening mammography this screening took place in US and Canada. All the mammograms are studied individually with the help of two medical experts. In the total population, the accuracy of digital and film mammography was similar for all but for women who are under 50 years of age got higher accuracy in digital mammography when compared to film mammography. This breast cancer detection diagnosis was done within fifteen months after we did the study entry, and following-up after ten months the mammogram is obtained after the study entry.

MRI plays a key role in detecting the breast cancer, and in that Contrast enhanced breast MRI are having major role in the evaluation and management of the breast cancer. Here Iman Washington et al., (2024) [10] introduced an article on MRI in this article they have discussed about all the MRI sequences, and also discussed about the uses of these MRI in medical, how they used all these MRI for detecting the breast cancer. This article also includes how the MRI is being processed and to make it useful for breast radiotherapy treatment. This study is highlighting the MRI and its contribution in effective decision making, and also includes the selecting process of correct candidates for breast therapy.

3. DATASET DETAILS

Here for our proposed model training we have used the KAU-BCMD where it stands for King Abdulaziz University- Breast Cancer Mammography Dataset, this dataset is available publicly and this dataset contains some collection of mammogram images and along with these images it also contains the annotations for every mammogram image. All of these images found in this dataset are designed in a way that is useful for research like for detecting breast cancer automatically and also made them for easy use in classification of BIRADS. Here the dataset we have taken contains four different types of categories of BIRADS like BIRAD1, BIRAD3, BIRAD4, and BIRAD5. In medical/clinical terms the BIRAD1 is interpreted as normal, whereas the other three categories BIRAD3, BIRAD4, BIRAD5 are interpreted as some suspicious and malignant abnormalities.

For our proposed work we have also treated the BIRAD1 category as normal class and for the other three have treated them as different types of breast abnormality. Here our dataset shows the imbalance in classes, in medical imaging this class imbalance is quite common. The BIRAD1 contains a large number of data samples in it when compared to other categories where these categories consist of fewer images. This data imbalance is considered as a big challenge in deep learning models because the data imbalance will result in model bias, where the algorithms may tend to be biased towards majority classes, this model bias will result in inefficient predictions of breast cancer. Each mammogram image present in our dataset have high resolution, which enables the model to extract each and every feature in detail for both local and globalized breast tissue patterns. All the images in our dataset undergoes a process called preprocessing this preprocessing is done by using some of the standardized techniques, this preprocessing includes resizing the dimensions of image. Preprocessing ensures the consistency across all the images and increases the model stability in feature extraction.

The KAU-BCMD dataset provides a different kinds of data images that are mammogram images, these mammogram images found in this dataset are very diverse and they cover multiple medical breast categories, overall this KAU-BCMD dataset is suitable for the model training and testing. This

Gives the effective results for our proposed model that is Stacked model using CNN-LSTM, even under imbalanced and balanced conditions.

4. PROPOSED METHODOLOGY

In our proposed stacked modelusing CNN-LSTM we have built aninteractive platform, where all the functionalities are controlled by the Admin, and also here for our proposed study we are following a dual step approach for the classification of breast cancer mammograms. This proposed method combines the ResNet50 for feature extraction, SMOTE for data balancing, and along with that we are using a Hybrid model that integrates CNN-LSTM to capture spatial and temporal patterns found in the mammogram dataset images. The administrator can be able to do the prediction,here in our proposed system the administrator will login to the system, then he can directly predict the results just by uploading the test images that we have taken separately. As for the model training and all we are using jupyter notebook in that we will do all the steps needed for the effective model generation for breast cancer classification. The process in our proposed work is consists of some steps that steps includes dataset uploading, feature extraction, analyzing imbalanced data, data balancing using SMOTE, model development and training, finally the last step is to evaluate the performance and evaluates the prediction.

Here in the first step of dataset loading all the mammogram images that are found in the KAU-BCMD dataset are uploaded into the model through the pipeline called preprocessing that we have created in the jupyter notebook, here in this preprocessing every mammogram image in the dataset is resized to the input dimensions this resizing is done with the help of ResNet50. After resizing the images are normalized with the help of VGG16, this normalization is done to ensure the consistency in image distribution, and after normalizing these images are labelled to their corresponding BIRAD classes, for example the image from the BIRAD1 class are labelled as normal, similarly all the other images in other BIRADS are labelled according to their corresponding BIRAD classes.

The second step in our proposed system includes feature extraction, this feature extraction is done with the help of a ResNet50 model which is pre-trained to extract spatial features from every mammogram image. Here the model collects the high level features like texture and characteristics which are related to the breast tissue patterns with the help of the ResNet50 model weights. Finally, at the end the pooling layer will give some feature vector for each image, that form a matrix X where it contains the features and all the labels are stored in the Y vector.

The next step is to analyze the imbalanced data and visualizing it, here in this step all the classes that we have in our dataset are analyzed and visualized in the form of a bar graph, the bar graph represents the domination of BIRAD1, this is because the other classes contains fewer images when compared to the BIRAD1 class images. This imbalance representation tells that we need an advanced technique for the data imbalance so that we can prevent bias in the algorithms and reduce the false positives and false negatives for classes with fewer images. After analyzing and handling this imbalanced data the next step in our proposed method is a balancing mechanism called dual SMOTE balancing, here all the features are oversampled with the help of synthetic minority, this SMOTE technique gives a balanced data where this balanced data was split into 80% and 20% where the 80% is used for training the model and 20% is used for the testing.

After the dataset splitting, we are going to build our Stacked model CNN-LSTM to improve the temporal the feature extraction and pattern recognition we are developing this stacked model, even though the mammogram image that we have found in our dataset are static, the small differences in the tissues can act as temporal changes. So to handle these temporal changes we are using CNN with LSTM where the CNN extracts the spatial features and the LSTM consider them as sequential patterns.

The proposed stacked model is giving the accuracy of 99.66%, outperforming all the existing balanced and imbalanced CNN models. To deploy this model a flask web application is built and in that the system allows the users to upload mammogram images present in the test dataset and receive real-time predictions, the test results shows that the proposed CNN-LSTM model is identifying the BIRAD1, BIRAD3, BIRAD4, and BIRAD5 classes accurately.

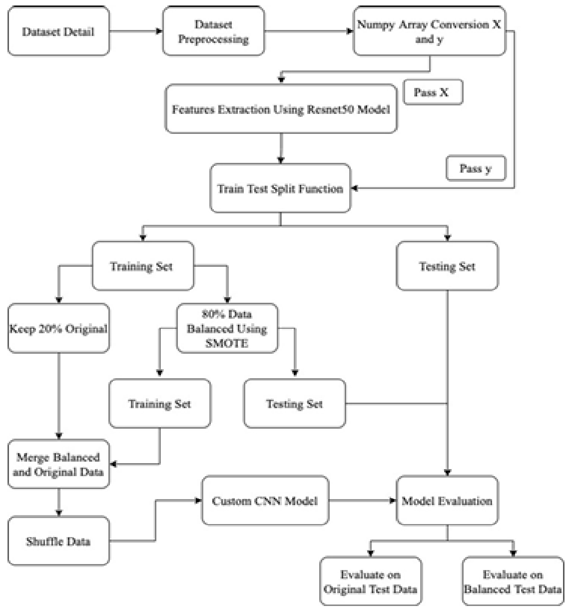

Figure 1: System Architecture of Proposed Model

5. RESULT AND DISCUSSION

Here the after uploading the dataset the classes present in the dataset are distributed and we can visualize that in graphical format as shown in figure [2], it represents that BIRAD1 class is dominating the other classes this is because the other BIRD3, BIRAD4, and BIRAD5 are containing fewer mammogram images whereas the BIRAD1 is containing large number of mammogram images. This tells that the dataset is strongly imbalanced that imbalance will affect the model training.

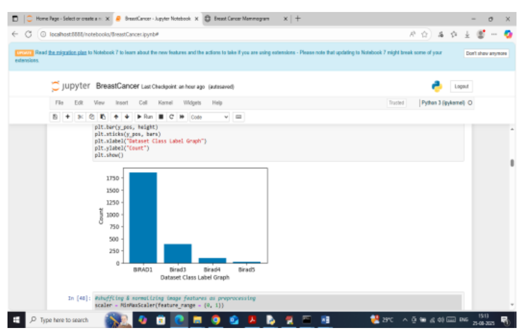

Figure 2: Dataset Class Label Graph

The existing fully connected CNN model was trained on both balanced and imbalanced data, here in figure [3] we can see the results of the CNN model on original imbalanced dataset. the confusion matrix here in this showing that the model predicted correctly on BIRAD1 dataset but when it comes to the other BIRAD classes the model produced some misclassifications.

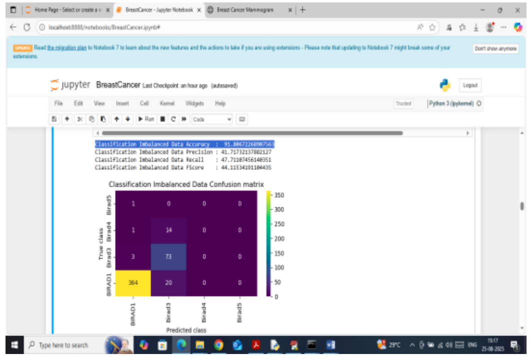

Figure 3: Confusion Matrix of the Existing CNN model on Imbalanced Data

After getting the results of CNN model on imbalanced data we have applied the SMOTE technique on the imbalanced data to balanced data, it is applied in two stages one is on the complete dataset and the other one is on the 80% of the training data that we have after splitting the dataset into two parts. After balancing the model gave improved performance, in figure [4] we can see that the confusion matrix showing equal prediction on all of the BIRAD classes and it is giving the accuracy of 99.06% all the metrics got equal results.

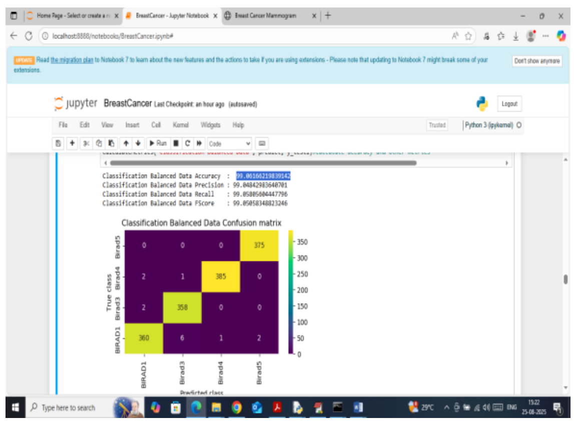

Figure 4: Confusion Matrix of the Existing CNN model on Balanced Data

To improve the temporal and spatial feature extraction, we have used the proposed stacked model integrating an LSTM and CNN. This model achieved 99.66% of accuracy as shown in figure [5], the performance metrics of the proposed model is greater than the existing models, the confusion matrix in figure [5] is showing that almost all of the BIRAD classes got decent classification.

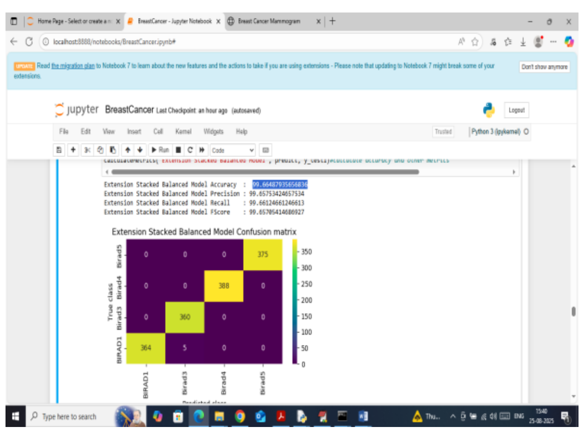

Figure 5: Confusion Matrix of the Proposed Stacked CNN+LSTM model

Comparative Performance Summary

The comparison of the proposed stacked model's accuracy, precision, recall, and F1score are represented in the figure [6].

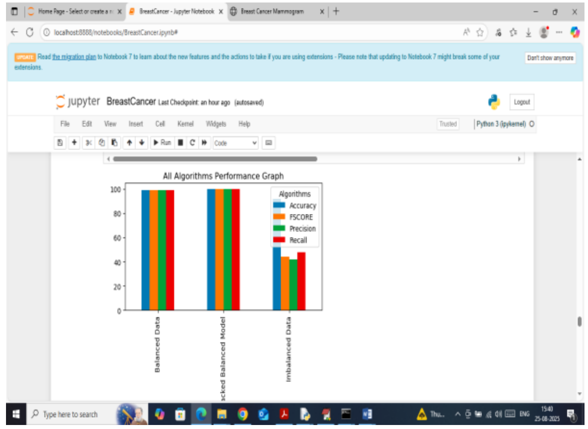

Figure 6: Comparison Graph of All the Models

The datasetcategorizationwas evaluated using CNN and CNN+LSTM. Table 1 shows the performance metrics, telling how well the fully connected CNN and CNN with LSTM Algorithm performs.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Fully connected CNN	99.06	99.04	99.05	99.05
CNN +LSTM	99.66	99.65	99.66	99.65

Table 1: Model Performance Metrics

6. DISCUSSION

Many of the researchers like up to 48% of researchershave utilized the mammogram image datasets, to detect and classify the breast cancer. The researchers have applied a wide range of ML algorithms on different types of datasets, some of the researchers most likely to be 33% of researchers have madeuse of histological images for the breast cancer classification and detection, and many of the studies utilizeddatasets that are accessed openly, up to eleven percent of the researchers have made theuse of ultrasound for breast cancer, and only 4% used thermography images. patients who are suffering from Breast cancer always expect correct results. Using mammogram images improved the accuracy in breast cancer classification and detection. initially we got the lower accuracy. This lower accuracy on imbalanced data is pointing out how the dataset can mislead the classification and prediction results. The DL model in breast cancer classification significantly improve the accuracy, by applying the SMOTE technique we effectively improved the accuracy the stacked model is giving the accuracy of 99.66%, this results confirm that synthetic oversampling gives enhanced results in identifying the minor pattern that present in the dataset. the proposed hybrid stacked model is very effective for real-time predictions in medical decision making.

7. CONCLUSION

In conclusion, this paper presents a DL based Stacked model integrating CNN with LSTM and along with that it is also integrates ResNet50 and SMOTEto classify the breast cancer in women,this paperindicates the challenges of both balanced and imbalanced datasets. feature extraction is done with the help of ResNet50 and data balancing is done by applying the SMOTE technique, here we have takendataset to test the stacked model's performance on both imbalanced and balanced test data. The proposed stacked modelachievedan accuracy results of 99.66% on the balanced dataset andachieved an accuracy results of 91.80% on the imbalanced data, representing its ability toadaptin real-world scenarios.ourpaperpoints out the importance of handling imbalanced data in medical diagnostic systems and also our paper provides an easy to use platform toclassify and detect the breast cancer from the available mammogram images.Even though our stacked modelmentions the improvements in handling imbalanced data and improvement inclassifying the breast cancer, but still it implies some drawbacks. Here we are mostly depending upon the pretrained models like ResNet50 and VGG16, these pretrained model may limit theirability of adapting to diverse image datasets.

Additionally, the proposed stacked model's performance may not be the same for different types of dataset, and also for the synthetic data generation the SMOTE technique may not be able to capture the real-world differences and changes.

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