BREAST CANCER DETECTION: A DEEP LEARNING APPROACH

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OVERVIEW

- Introduction: Breast cancer is the second leading cause of death in women. Breast cancer mortality is reduced by early identification and treatment.
- Mammography: Renowned for breast cancer screening, mammography excels in early detection, capturing irregularities like lumps and calcification sites.
- Challenges: The efficacy of mammography faces obstacles in dense breast tissue, complicating the detection of malignant masses.
- Our Solution: We propose a sophisticated deep learning system designed to analyze mammographic images and predict breast cancer categorization.

Implementation of this project can help in the following ways:

- Help physicians for early detection to maximize patients' survival rate.
- Minimize the number of "untrained eyes" that is wrong interpretations and increase the accuracy of screening.
- Prevent late treatments as well as unnecessary treatments in case of false positives.
- One would be able to overcome the dependency of pathologist in the places where no experts are available.

DATASET

The dataset to be used in this project is put together by Mendeley Data. It is free to use and open source. The dataset contains mammography with benign and malignant masses.

- INbreast Total Images : 7632
- MIAS (Mammographic Imaging Analysis society) Total Images : 3816

- Training and Validation set contains : 11448
- Test set contains : 2349
- Image Size : 227 * 227

BACKGROUND

Year	Model Name	Accuracy Achieved
2017	K- Nearest Neighbor	**83%-89%**
2019	FrCN (Convolutional Network)	**90.96%**
2017	YOLOv5 Modified	**89.50%**
2019	Deep-CNN with Transfer Learning	**91.54**
2018	CNN Inception-v3	**87%**
2019	CNN and TL Classification (Eight Pretrained Models)	**85%-91%**
2021	Hybrid Model (Mobilenet, ResNet50, Alexnet)	**92.6%**
2020	Four Different CNN Architectures (VGG19, InceptionV3, ResNet50, VGG16)	**88.32%**
2019	AlexNet and SVM with Data Augmentation	**87.2%**

APPROACH

- Built a CNN Model
- Transfer Learningng with Pretrained Models- DenseNet121, InceptionV3, MobileNetV2, ResNet50

CNN APPROACH

- **Image Processing :**
  1. Image transformations: reshape, Rotation.
  2. Data Augmentation
- **Feature Extraction :**
  1. Patterns and textures extracted using combination of convolution and max pooling layers.
  2. CNN filters and their weights, are features that are used at the time of testing for model evaluation.
- **Classification :**
  1. Places an image into the respective class (benign or malignant)
  2. Classified using a fully connected layer using an activation function such as Softmax.

CNN ARCHITECTURE

```
from keras.layers import Flatten
# define the larger model
def larger_model():
    # create model
    model = Sequential()
    model.add(Conv2D(32, (3, 3), padding="same",input_shape=(92,140,3), activation='relu'))
    #model.add(Conv2D(32, (3, 3), activation='relu',padding = 'same'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Conv2D(32, (3, 3), activation='relu',padding = 'same'))
    #model.add(Conv2D(64, (3, 3), activation='relu',padding = 'same'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Conv2D(64, (3, 3), activation='relu',padding = 'same'))
    #model.add(Conv2D(128, (3, 3), activation='relu',padding = 'same'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.5))
    model.add(Flatten())
    model.add(Dropout(0.5))
    model.add(Dense(64, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(64, activation='relu'))
    model.add(Dropout(0.5))
    #model.add(Dense(50, activation='relu'))
    #model.add(Dropout(0.2))
    model.add(Dense(num_classes, activation='softmax'))
    # Compile model
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model
```

Basic CNN : 86.4 %
Adding more layers (64 channels + 3x3 kernel) : 90 %
Architecture + Image Augmentation : 91 %
Final Accuracy :

1. **MIAS : 92.02 %**

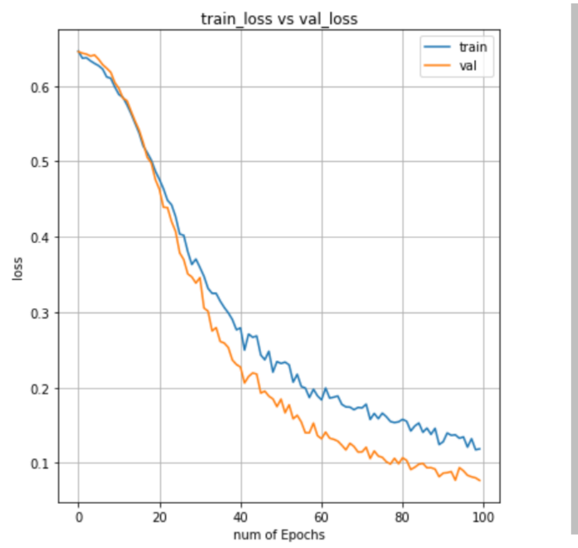
2. **INbreast : 97.45 %**

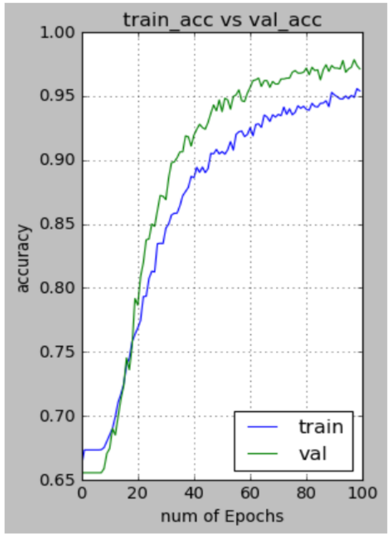
TRANSFER LEARNING APPROACH

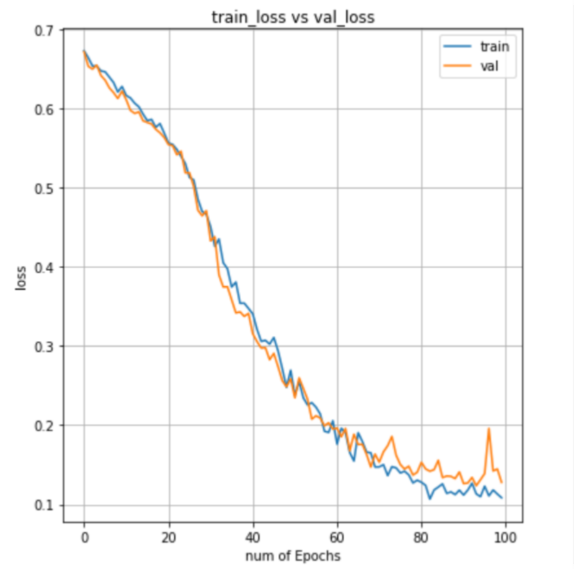
```
base_Neural_Net= InceptionV3(input_shape=(224,224,3), weights='imagenet', include_top=False)
model=Sequential()
model.add(base_Neural_Net)
model.add(Flatten())
model.add(BatchNormalization())
model.add(Dense(256,kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(2,activation='softmax'))

for layer in base_Neural_Net.layers:
    layer.trainable = False
    c1=PlotLossesKeras()

model.compile(optimizer='adam',loss='categorical_crossentropy', metrics=['accuracy','AUC'])
history=model.fit(x_train,y_train,epochs=100,callbacks=[c1,c3],batch_size=16)
```

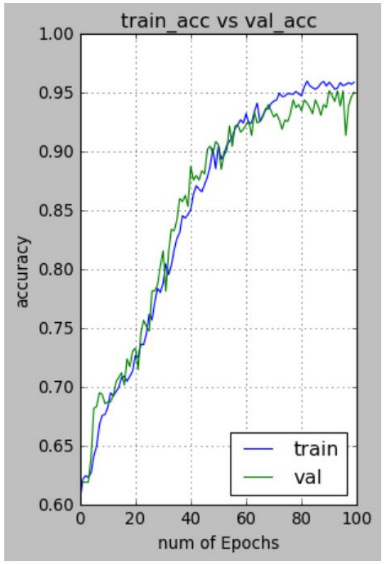
Pre-trained Models	Accuracy	
	Inbreast	MIAS
Densenet121	93.98%	88.50%
MobileNetV2	91.03%	87.34%
InceptionV3	93.09%	88.92%
ResNet50	94.32%	90.39%

PERFORMANCE GRAPHS









Training loss and validation loss -

- Loss start with a high value and decrease while training proceeds.
- Difference in saturation levels of Training Loss and Validation Loss is 0.2, within the permissible range for a network to avoid underfitting or overfitting.

Training accuracy and validation accuracy -

- Accuracy starts to increase with the number of epochs, and ultimately saturates.
- No underfitting and overfitting, as validation accuracy and training accuracy curves are similar in distribution.

CLASSIFICATION REPORT

MIAS Dataset

	precision	recall	f1-score	support
0	0.92	0.95	0.94	467
1	0.92	0.87	0.89	285
accuracy			0.92	752
macro avg	0.92	0.91	0.91	752
weighted avg	0.92	0.92	0.92	752

INbreast Dataset

	precision	recall	f1-score	support
0	0.95	0.98	0.96	526
1	0.99	0.97	0.98	1001
accuracy			0.97	1527
macro avg	0.97	0.98	0.97	1527
weighted avg	0.97	0.97	0.97	1527

Precision :

A probabilistic measure to determine whether a positive case, defined on our terms, actually belongs to positive case.

Recall and F1 score :

A probabilistic measure to determine if an actual positive case is correctly classified with the positive class.

F1 score is calculated as the geometric mean between precision and recall.

CONCLUSION AND FUTURE SCOPE

- We have compared our result (92.02% and 97.45% validation accuracy from test set) with transfer learning models and several published studies, we found out our model outperforms the previous results.

Models	Accuracy	
	Inbreast	MIAS
Densenet121	93.98%	88.50%
MobileNetV2	91.03%	87.34%
InceptionV3	93.09%	88.92%
ResNet50	94.32%	90.39%
OUR CNN	97.45%	92.02%

- Results are insensitive to the resolution of images.
- Scope to implement auto-encoders instead of manually reducing image size.
- It can compress data without losing the prominent features.
- Classified breast cancer tissues into two classes benign and malignant with

  Accuracy of 92.02 % for MIAS

  Accuracy of 97.45% for Inbreast datasets.


THANK YOU