



Breast Cancer Detection using Deep Learning

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Abstract

Breast cancer remains one of the most prevalent and life-threatening diseases globally. Early detection plays a crucial role in improving patient outcomes and survival rates. In this project, we explore the application of deep learning techniques, specifically feedforward neural networks, for breast cancer detection using mammographic images. Leveraging a dataset comprising mammograms from diverse patient populations, our model aims to accurately classify images as indicative of malignant or benign tumors. Through extensive experimentation and validation, we demonstrate the efficacy of our approach in providing accurate and timely diagnosis, thus contributing to improved patient care and clinical decision-making in breast cancer detection.

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1. Introduction and Subject description:

Breast cancer is a significant health concern globally, particularly in the United States, where a woman is diagnosed with breast cancer every two minutes. It stands as the leading cause of death for women worldwide, claiming over 40,000 lives annually from 220,000 medical diagnoses. However, advancements in early detection, improved screening methods, and heightened awareness since the 1990s have contributed to a decrease in breast cancer deaths. Notably, women who undergo early screening have a 53% higher chance of survival.

In women over 50, breast cancer ranks as the second most common cause of cancer-related death. Factors such as prolonged night shift work and excessive use of antiperspirants, deodorants, and underarm shaving have been associated with increased breast cancer risk. Multi-drug resistance poses a significant challenge in treatment, contributing to low survival rates among breast cancer patients.

Efforts in medical research have explored various techniques for breast cancer detection. The current approach focuses on utilizing Cellular Automata (CA) for segmentation, offering a visually compelling method compared to other computational techniques like neural networks. Cellular Automata, discrete spatial systems, operate with internal states updated based on local transition rules. This method showcases promise in detecting suspicious regions in mammograms, aligning with the needs of medical professionals. [1]

Experts conducted an extensive review of both deep learning (DL) and traditional machine learning (ML) approaches for breast cancer prediction. They analyzed a total of 8 papers in DL and 27 papers in ML, revealing that the majority of the literature primarily utilized imaging processes, with only a small fraction incorporating genetics. Similarly, [2] examined various imaging methods, specifically mammography, for breast cancer diagnosis, while Gupta et al. [3] provided an overview of different systems and techniques for early breast cancer detection, including radar-based imaging and microwave tomography.

Furthermore, Oyelade et al. [4] explored deep learning-based methods for breast cancer diagnosis from digital mammography, while Husaini investigated machine learning techniques and thermography for detecting breast cancer issues. The latter study delved into multiple ML methods for processing thermographic images related to breast cancer.

Upon reviewing the existing literature on deep learning-based methods for breast cancer detection, it is apparent that the predominant focus lies on image-based approaches. While traditional ML methods are often emphasized in previous studies, the coverage of

deep learning-based techniques remains limited, lacking a comprehensive and systematic analysis of existing approaches.

2. Materials and Methods

2.1. Dataset Overview. The WBDC[6] dataset comprises 569 instances, categorized into 357 benign and 212 malignant cases. Each instance includes an ID number, diagnosis (B = benign, M = malignant), and 30 features. These features are derived from digitized images of fine needle aspirates (FNA) of breast masses, as illustrated in **Figure 1**. Specifically, the ten real-valued features are 1. Radius, 2. Texture, 3. Perimeter, 4. Area, 5. Smoothness, 6. Compactness, 7. Concavity, 8. Concave points, 9. Symmetry, 10. Fractal dimension and are computed for each cell nucleus. For each image, the mean, standard error, and “worst” (the mean of the three largest values) of these features are calculated, resulting in a total of 30 features [5].

2.2 Feedforward Neural Networks. Feedforward Neural Networks (FNNs) are a type of artificial neural network (ANN) that are widely used in machine learning and artificial intelligence applications. The fundamental characteristic of FNNs is their unidirectional flow of information, where the data moves in only one direction, from the input layer to the output layer, as represented in **Figure 2**, without looping back. This differentiates FNNs from other types of ANNs, such as recurrent neural networks, which allow for feedback connections.

In a typical FNN, the input layer receives the external data or features that the network will process. These inputs are then passed to the hidden layer(s), where the actual processing occurs. The hidden layer(s) contain artificial neurons, which are mathematical functions that model the behavior of biological neurons. These neurons perform computations on the input data, using weights and biases that are adjusted during the training process. The output of the hidden layer(s) is then sent to the output layer, which produces the final result of the network's computation.

The architecture of FNNs can vary depending on the number of hidden layers employed. Simple FNNs may only have one hidden layer, while more complex networks can have multiple hidden layers. The use of multiple hidden layers allows for the modeling of more complex relationships between the input and output data, and is the basis for deep learning approaches.

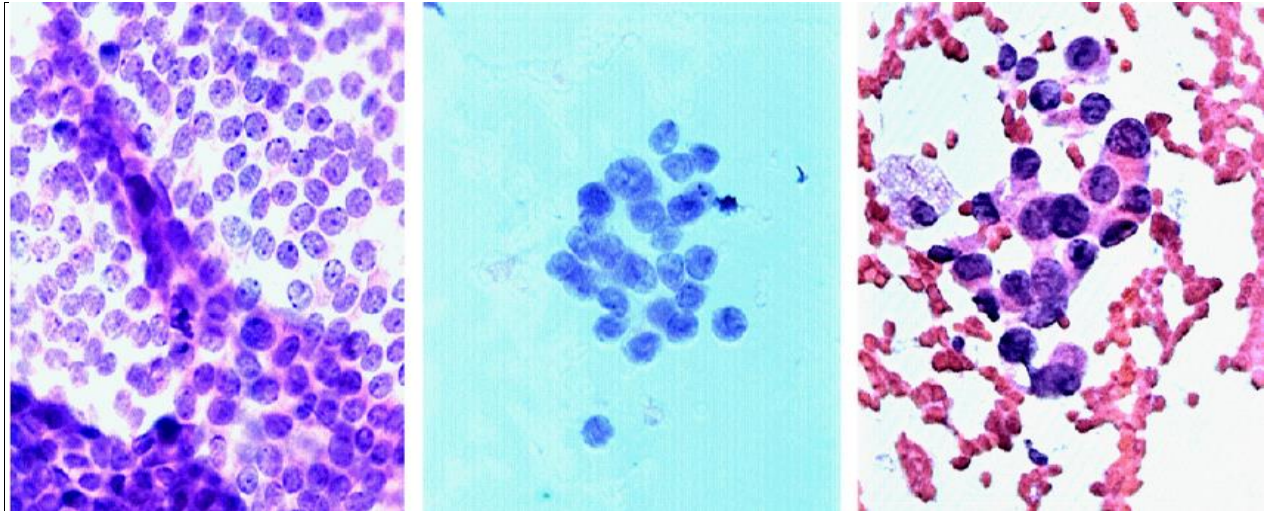


Figure 1: FNA breast biopsies, left:benign, center and right:malign

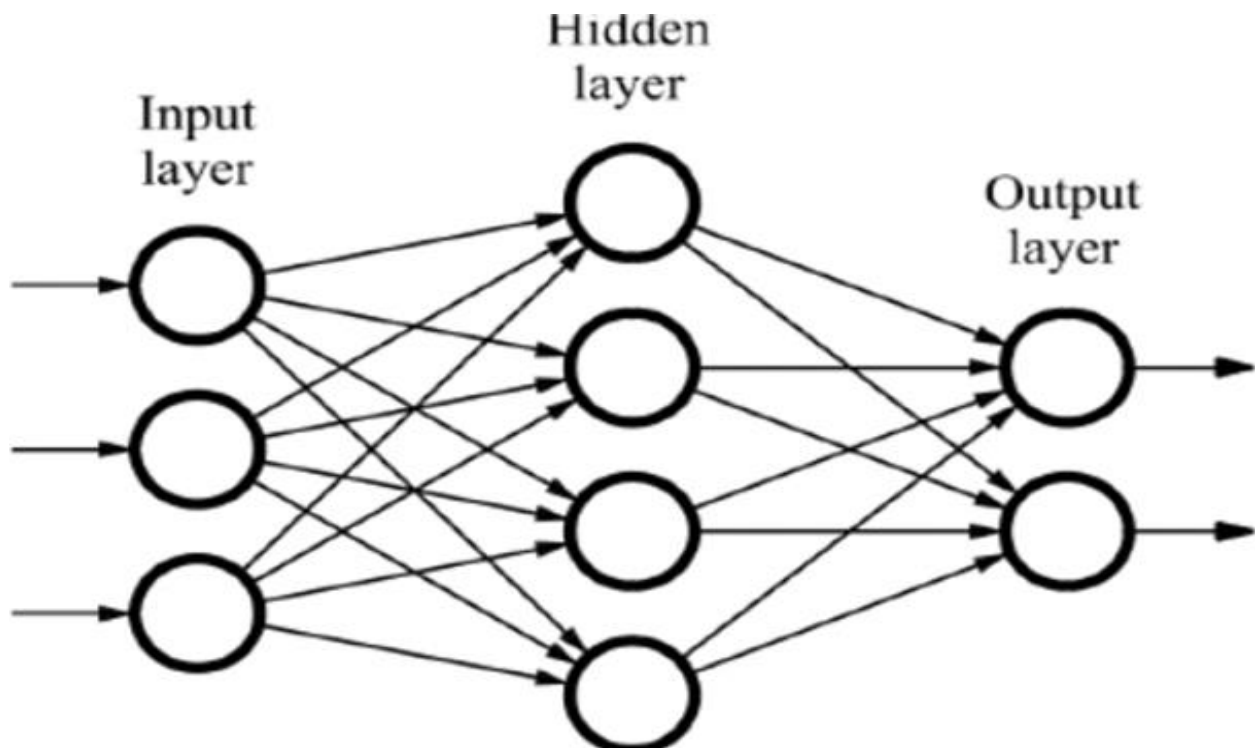


Figure 2: Feedforward neural Networks

3. Methodology and Implementation

Project description: Breast cancer detection using machine learning involves the development and implementation of algorithms that analyze mammograms, to identify potential abnormalities indicative of breast cancer. Machine learning

models are trained on large datasets of labeled images to learn patterns and features associated with both normal and cancerous breast tissue.

Breast cancer segmentation can be addressed such different approaches such as game theory, machine learning algorithms and others.

Problem statement analysis: Diagnose whether the patient has cancer or not using the attributes provided

- Attributes and diagnosis as a csv file
- Attributes are used from a digitized image of a FNA(fine needle aspirate) of a breast mass
- Dataset used:
<https://archive.ics.uci.edu/dataset/17/breast+cancer+wisconsin+diagnostic>
- Binary problem: B(benign), M(malign)

Strategy: Use the attributes given as input data and the two diagnosis labels: B and M as output on the training data. Then test the accuracy of the model on the testing data. The training data and the testing data will never have the overlapping data as to test the accuracy as strictly as possible.

3.1 Imports and data parsing

```
1 import pandas as pd
2 import matplotlib.pyplot as plt
3 import seaborn as sns
4 import numpy as np
5 from sklearn.preprocessing import LabelEncoder, MinMaxScaler
6 from sklearn.model_selection import train_test_split
7 from keras.models import Sequential
8 from keras.layers import Dense, Dropout, Activation
9 from sklearn.metrics import confusion_matrix
10
```

The provided code imports essential Python libraries for data analysis and visualization: Pandas for data manipulation and analysis, Matplotlib for diverse plot creation, Seaborn for statistical visualization, and NumPy for numerical computations and array operations. These libraries collectively enable efficient data analysis, manipulation, and visualization in Python.

```

1 usage
12 def load_data(file_path):
13     dt = pd.read_csv(file_path)
14     dt.drop(dt.columns[32], axis=1, inplace=True)
15     print(dt)
16     return dt
17
18

```

	count	mean	std	min	25%	\
842302	568.0	3.042382e+07	1.251246e+08	8670.000000	869222.500000	
17.99	568.0	1.412049e+01	3.523416e+00	6.981000	11.697500	
10.38	568.0	1.930533e+01	4.288506e+00	9.710000	16.177500	
122.8	568.0	9.191475e+01	2.428585e+01	43.790000	75.135000	
1001	568.0	6.542798e+02	3.519238e+02	143.500000	420.175000	
0.1184	568.0	9.632148e-02	1.404601e-02	0.052630	0.086290	
0.2776	568.0	1.040360e-01	5.235523e-02	0.019380	0.064815	
0.3001	568.0	8.842731e-02	7.929422e-02	0.000000	0.029540	
0.1471	568.0	4.874629e-02	3.861717e-02	0.000000	0.020310	
0.2419	568.0	1.810549e-01	2.731942e-02	0.106000	0.161900	
0.07871	568.0	6.276960e-02	7.034862e-03	0.049960	0.057697	
1.095	568.0	4.039576e-01	2.760385e-01	0.111500	0.232375	
0.9053	568.0	1.217402e+00	5.519793e-01	0.360200	0.833150	
8.589	568.0	2.855984e+00	2.009288e+00	0.757000	1.605000	
153.4	568.0	4.013802e+01	4.528241e+01	6.802000	17.850000	
0.006399	568.0	7.042109e-03	3.005043e-03	0.001713	0.005166	
0.04904	568.0	2.543666e-02	1.789658e-02	0.002252	0.013048	
0.05373	568.0	3.185527e-02	3.019872e-02	0.000000	0.015062	
0.01587	568.0	1.178896e-02	6.173350e-03	0.000000	0.007634	
0.03003	568.0	2.052560e-02	8.264041e-03	0.007882	0.015128	
0.006193	568.0	3.790682e-03	2.646484e-03	0.000895	0.002244	
25.38	568.0	1.625315e+01	4.822320e+00	7.930000	13.010000	

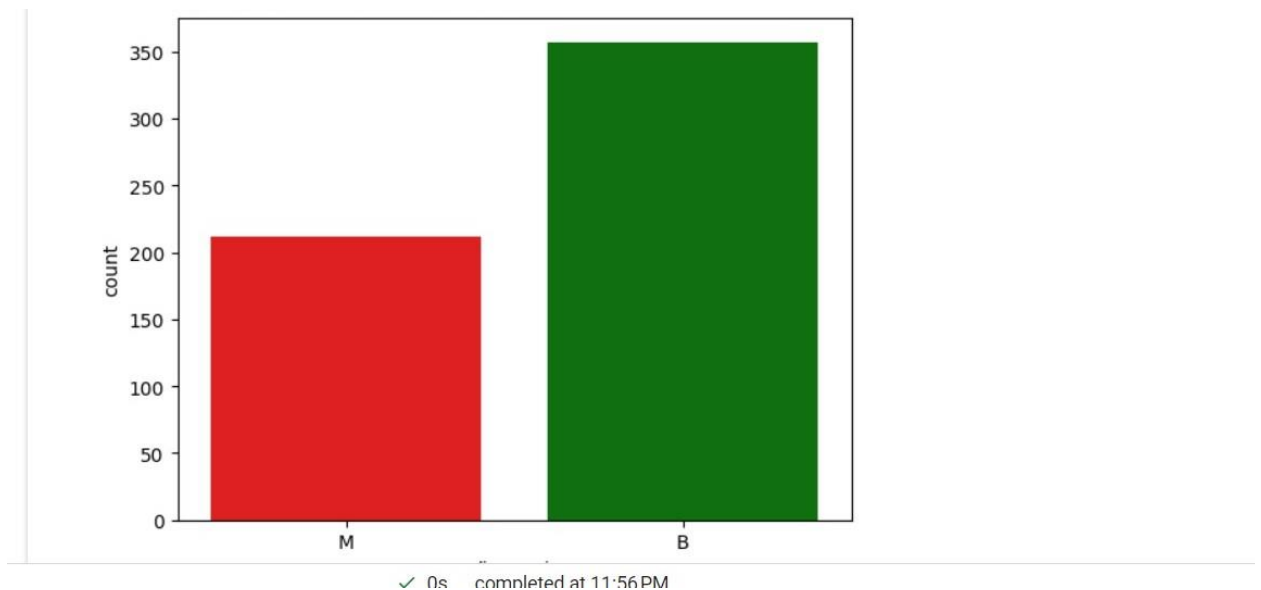
✓ 0s completed at 11:32 PM

This code utilizes the pandas library to read the dataset from a CSV file and store it in a DataFrame called dt. The describe() method provides key statistical metrics such as count, mean, standard deviation, and quartiles for each numerical column in the dataset. By transposing the resulting DataFrame (T), the statistical summary is presented with column-wise statistics aligned, aiding in its interpretation. This code thus lays the groundwork for a rigorous academic exploration of the Wisconsin Breast Cancer Study data.

```

1 usage
9 def plot_countplot(dt):
10     custom_palette = {"M": "red", "B": "green"}
11     sns.countplot(x="diagnosis", data=dt, palette=custom_palette)
12     plt.show()
13

```

This code utilizes seaborn to create a count plot (`sns.countplot()`) showcasing the volume of malignant (denoted as "M") and benign (denoted as "B") tumors in the dataset. The custom color palette `custom_palette` assigns red color to malignant tumors and green color to benign tumors for visual clarity. Additionally, labels for the x-axis ("Diagnosis") and y-axis ("Count") are added, along with a descriptive title ("Distribution of Malignant and Benign Tumors"). Finally, the plot is displayed using `plt.show()`. This visualization aids in understanding the distribution of tumor diagnoses within the study population.

3.2 Data processing

```
18
19 1 usage
20 def encode_diagnosis(dt):
21     y = dt['diagnosis'].values
22     print("Diagnosis before encoding are: ", np.unique(y))
23     labelencoder = LabelEncoder()
24     Y = labelencoder.fit_transform(y)
25     print("Labels after encoding are: ", np.unique(Y))
26     return Y
27
```

```

Data distribution: B    357
M    212
Name: diagnosis, dtype: int64
Diagnosis before encoding are: ['B' 'M']
Labels after encoding are: [0 1]

```

This code snippet showcases the process of encoding the 'diagnosis' column in the dataset. It begins by printing the distribution of diagnoses to understand their frequency in the dataset. Subsequently, it extracts the 'diagnosis' column values and prints the unique values before encoding. Utilizing sklearn. Preprocessing. LabelEncoder, the diagnoses are encoded into boolean data, where 'M' is encoded as 1 and 'B' as 0. Finally, the unique encoded values are printed, illustrating the transformation achieved through encoding. This process aids in preparing the dataset for further analysis, particularly in machine learning tasks where categorical variables require numerical representation.

```

28 def preprocess_data(dt):
29     X = dt.drop(labels=["diagnosis", "id"], axis=1)
30     print(X.describe().T)
31     scaler = MinMaxScaler()
32     scaler.fit(X)
33     X = scaler.transform(X)
34     print(X)
35     return X
36

```

	count	mean	std	min	\
radius_mean	569.0	14.127292	3.524049	6.981000	
texture_mean	569.0	19.289649	4.301036	9.710000	
perimeter_mean	569.0	91.969033	24.298981	43.790000	
area_mean	569.0	654.889104	351.914129	143.500000	
smoothness_mean	569.0	0.096360	0.014064	0.052630	
compactness_mean	569.0	0.104341	0.052813	0.019380	
concavity_mean	569.0	0.088799	0.079720	0.000000	
concave points_mean	569.0	0.048919	0.038803	0.000000	
symmetry_mean	569.0	0.181162	0.027414	0.106000	
fractal_dimension_mean	569.0	0.062798	0.007060	0.049960	
radius_se	569.0	0.405172	0.277313	0.111500	
texture_se	569.0	1.216853	0.551648	0.360200	
perimeter_se	569.0	2.866059	2.021855	0.757000	
area_se	569.0	40.337079	45.491006	6.802000	
smoothness_se	569.0	0.007041	0.003003	0.001713	
compactness_se	569.0	0.025478	0.017908	0.002252	
concavity_se	569.0	0.031894	0.030186	0.000000	
concave points_se	569.0	0.011796	0.006170	0.000000	
symmetry_se	569.0	0.020542	0.008266	0.007882	
fractal_dimension_se	569.0	0.003795	0.002646	0.000895	
radius_worst	569.0	16.269190	4.833242	7.930000	
texture_worst	569.0	25.677223	6.146258	12.020000	
perimeter_worst	569.0	107.261213	33.602542	50.410000	
area_worst	569.0	880.583128	569.356993	185.200000	
smoothness_worst	569.0	0.132369	0.022832	0.071170	
compactness_worst	569.0	0.254265	0.157336	0.027290	
concavity_worst	569.0	0.272188	0.208624	0.000000	


```

[[0.52103744 0.0226581 0.54598853 ... 0.59846245 0.41886396
 [0.64314449 0.27257355 0.61578329 ... 0.23358959 0.22287813
 [0.60149557 0.3902604 0.59574321 ... 0.40370589 0.21343303
 ...
 [0.45525108 0.62123774 0.44578813 ... 0.12872068 0.1519087
 [0.64456434 0.66351031 0.66553797 ... 0.49714173 0.45231536
 [0.03686876 0.50152181 0.02853984 ... 0.25744136 0.10068215

```

This code segment showcases the process of encoding the 'diagnosis' column in the dataset. It begins by printing the distribution of diagnoses to understand their frequency in the dataset. Subsequently, it extracts the 'diagnosis' column values and prints the unique values before encoding. Utilizing `sklearn.preprocessing.LabelEncoder`, the diagnoses are encoded into boolean data, where 'M' is encoded as 1 and 'B' as 0. Finally, the unique encoded values are printed, illustrating the transformation achieved through encoding. This process aids in preparing the dataset for further analysis, particularly in machine learning tasks where categorical variables require numerical representation.

This epitomizes the foundational procedures in data analysis, spanning from the initial loading and preprocessing of the dataset to conducting exploratory data analysis (EDA). It represents a systematic methodology for comprehensively understanding the Wisconsin Breast Cancer Study dataset, thereby establishing a solid foundation for subsequent analyses and insights within the realm of breast cancer research.

```

1 usage
38 def split_data(X, Y):
39     X_train, X_test, y_train, y_test = train_test_split(*arrays: X, Y, test_size=0.25, random_state=42)
40     print("Training data is:", X_train.shape)
41     print("Testing data is:", X_test.shape)
42     return X_train, X_test, y_train, y_test
43
44

```

```

Training data is: (483, 31)
Testing data is: (86, 31)

```

This code snippet encompasses a crucial phase in machine learning—splitting the dataset into training and testing subsets. Utilizing the `train_test_split` function from `scikit-learn`, the dataset is divided into training and testing sets to facilitate model training and evaluation. A test size of 15% is specified, indicating that 15% of the data will be reserved for testing, while the remaining 85% will be utilized for training. Additionally, a random state of 42 ensures reproducibility of the split. The subsequent `print` statements provide insights into the dimensions of the resulting training and testing datasets, essential for understanding the data partitioning process within the breast cancer research project.

3.3 Model building and training

```
1 usage
45 def build_model():
46     model = Sequential()
47     model.add(Dense(units=16, input_dim=30, activation='relu'))
48     model.add(Dropout(0.2))
49     model.add(Dense(1))
50     model.add(Activation('sigmoid'))
51     model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
52     print(model.summary())
53     return model
54
55
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 16)	512
dropout (Dropout)	(None, 16)	0
dense_2 (Dense)	(None, 1)	17
activation (Activation)	(None, 1)	0

=====
Total params: 529 (2.07 KB)
Trainable params: 529 (2.07 KB)
Non-trainable params: 0 (0.00 Byte)

None

The provided code initializes a neural network model for binary classification tasks using Keras. It comprises an input layer with 31 features, a hidden layer with 16 units using the ReLU activation function, and an output layer with a single unit using the sigmoid activation function. Dropout regularization is incorporated to prevent overfitting by randomly dropping 20% of input units during training. The model is compiled with binary cross-entropy loss, Adam optimizer, and accuracy metric for evaluation. Lastly, `model.summary()` prints a summary detailing the architecture, parameters, and connections within the neural network model.

ReLU (Rectified Linear Activation):

ReLU is an activation function commonly used in neural networks. It replaces negative values with zero and leaves positive values unchanged. Mathematically, ReLU is defined as $f(x) = \max(0, x)$. The main advantage of ReLU is that it helps alleviate the vanishing gradient problem, where gradients become extremely small during backpropagation, by enabling faster and more effective training of deep neural networks.

Sigmoid Activation:

The sigmoid activation function is commonly used in binary classification tasks. It squashes the output to a range between 0 and 1, interpreting the output as the probability of the positive class. Mathematically, the sigmoid function is defined as $f(x) = 1 / (1 + e^{-x})$.

Binary Cross-Entropy Loss:

Binary cross-entropy is a loss function commonly used in binary classification tasks. It measures the dissimilarity between the predicted probabilities and the actual binary labels. In the context of this neural network, the binary cross-entropy loss function is used to quantify the difference between the predicted probability distribution (using the sigmoid activation function) and the true binary labels.

Adam Optimizer:

Adam is an adaptive learning rate optimization algorithm commonly used for training deep neural networks. It combines the benefits of two other popular optimization techniques: RMSProp and AdaGrad. Adam adapts the learning rate for each parameter individually, based on estimates of the first and second moments of the gradients, resulting in more effective training and faster convergence.

Accuracy Metric:

Accuracy is a commonly used metric for evaluating classification models. It measures the proportion of correctly classified instances out of the total number of instances. In the context of this neural network, the accuracy metric is used to

assess the performance of the model in correctly predicting the binary labels (0 or 1) for the given dataset.

```
1 usage
```

```
def train_model(model, X_train, y_train, X_test, y_test):  
    history = model.fit(X_train, y_train, verbose=1, epochs=100, batch_size=64,  
                        validation_data=(X_test, y_test))  
    return history
```

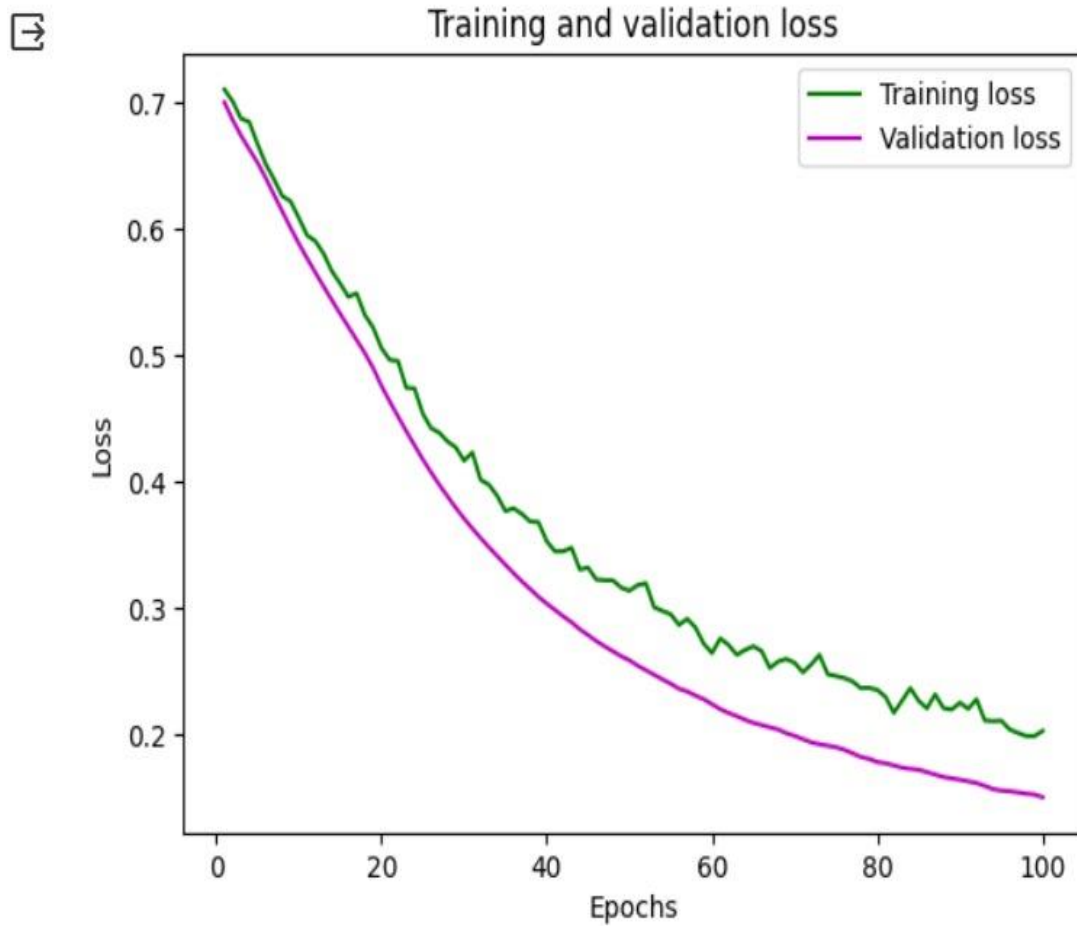
```
Epoch 1/100  
7/7 [=====] - 1s 35ms/step - loss: 0.7108 - accuracy: 0.5751 - val_loss: 0.7007 - val_accuracy: 0.6014  
Epoch 2/100  
7/7 [=====] - 0s 10ms/step - loss: 0.7015 - accuracy: 0.5657 - val_loss: 0.6867 - val_accuracy: 0.6294  
Epoch 3/100  
7/7 [=====] - 0s 7ms/step - loss: 0.6878 - accuracy: 0.5986 - val_loss: 0.6744 - val_accuracy: 0.6783  
Epoch 4/100  
7/7 [=====] - 0s 7ms/step - loss: 0.6852 - accuracy: 0.6009 - val_loss: 0.6636 - val_accuracy: 0.7413  
Epoch 5/100  
7/7 [=====] - 0s 7ms/step - loss: 0.6678 - accuracy: 0.6878 - val_loss: 0.6531 - val_accuracy: 0.7832  
Epoch 6/100  
7/7 [=====] - 0s 10ms/step - loss: 0.6519 - accuracy: 0.7418 - val_loss: 0.6407 - val_accuracy: 0.8531  
Epoch 7/100  
7/7 [=====] - 0s 8ms/step - loss: 0.6398 - accuracy: 0.7864 - val_loss: 0.6274 - val_accuracy: 0.8881  
Epoch 8/100  
7/7 [=====] - 0s 7ms/step - loss: 0.6265 - accuracy: 0.8146 - val_loss: 0.6144 - val_accuracy: 0.9231  
Epoch 9/100  
7/7 [=====] - 0s 10ms/step - loss: 0.6223 - accuracy: 0.7958 - val_loss: 0.6013 - val_accuracy: 0.9371  
Epoch 10/100  
7/7 [=====] - 0s 12ms/step - loss: 0.6093 - accuracy: 0.8521 - val_loss: 0.5889 - val_accuracy: 0.9231  
Epoch 11/100  
7/7 [=====] - 0s 8ms/step - loss: 0.5954 - accuracy: 0.8333 - val_loss: 0.5772 - val_accuracy: 0.9510  
Epoch 12/100  
7/7 [=====] - 0s 7ms/step - loss: 0.5908 - accuracy: 0.8380 - val_loss: 0.5660 - val_accuracy: 0.9510  
Epoch 13/100  
7/7 [=====] - 0s 7ms/step - loss: 0.5908 - accuracy: 0.8380 - val_loss: 0.5660 - val_accuracy: 0.9510  
Epoch 14/100  
7/7 [=====] - 0s 10ms/step - loss: 0.5809 - accuracy: 0.8239 - val_loss: 0.5549 - val_accuracy: 0.9441  
Epoch 15/100  
7/7 [=====] - 0s 10ms/step - loss: 0.5671 - accuracy: 0.8685 - val_loss: 0.5441 - val_accuracy: 0.9510  
Epoch 16/100  
7/7 [=====] - 0s 10ms/step - loss: 0.5573 - accuracy: 0.8685 - val_loss: 0.5333 - val_accuracy: 0.9231  
Epoch 17/100  
7/7 [=====] - 0s 7ms/step - loss: 0.5468 - accuracy: 0.8803 - val_loss: 0.5230 - val_accuracy: 0.9371  
Epoch 18/100  
7/7 [=====] - 0s 7ms/step - loss: 0.5494 - accuracy: 0.8592 - val_loss: 0.5125 - val_accuracy: 0.9371  
Epoch 19/100  
7/7 [=====] - 0s 10ms/step - loss: 0.5322 - accuracy: 0.8685 - val_loss: 0.5020 - val_accuracy: 0.9371  
Epoch 20/100  
7/7 [=====] - 0s 9ms/step - loss: 0.5223 - accuracy: 0.8779 - val_loss: 0.4903 - val_accuracy: 0.9231  
Epoch 21/100  
7/7 [=====] - 0s 8ms/step - loss: 0.5061 - accuracy: 0.8803 - val_loss: 0.4762 - val_accuracy: 0.9510  
Epoch 22/100  
7/7 [=====] - 0s 9ms/step - loss: 0.4967 - accuracy: 0.9014 - val_loss: 0.4638 - val_accuracy: 0.9441  
Epoch 23/100  
7/7 [=====] - 0s 7ms/step - loss: 0.4959 - accuracy: 0.8779 - val_loss: 0.4520 - val_accuracy: 0.9371  
Epoch 24/100  
7/7 [=====] - 0s 8ms/step - loss: 0.4747 - accuracy: 0.9014 - val_loss: 0.4404 - val_accuracy: 0.9441  
Epoch 25/100  
7/7 [=====] - 0s 7ms/step - loss: 0.2319 - accuracy: 0.9178 - val_loss: 0.1684 - val_accuracy: 0.9580  
Epoch 26/100  
7/7 [=====] - 0s 11ms/step - loss: 0.2210 - accuracy: 0.9131 - val_loss: 0.1665 - val_accuracy: 0.9650  
Epoch 27/100  
7/7 [=====] - 0s 9ms/step - loss: 0.2200 - accuracy: 0.9296 - val_loss: 0.1654 - val_accuracy: 0.9580  
Epoch 28/100  
7/7 [=====] - 0s 8ms/step - loss: 0.2253 - accuracy: 0.9225 - val_loss: 0.1643 - val_accuracy: 0.9650  
Epoch 29/100  
7/7 [=====] - 0s 8ms/step - loss: 0.2205 - accuracy: 0.9225 - val_loss: 0.1631 - val_accuracy: 0.9650  
Epoch 30/100  
7/7 [=====] - 0s 8ms/step - loss: 0.2281 - accuracy: 0.9249 - val_loss: 0.1617 - val_accuracy: 0.9720  
Epoch 31/100  
7/7 [=====] - 0s 8ms/step - loss: 0.2113 - accuracy: 0.9225 - val_loss: 0.1595 - val_accuracy: 0.9650  
Epoch 32/100  
7/7 [=====] - 0s 10ms/step - loss: 0.2108 - accuracy: 0.9319 - val_loss: 0.1569 - val_accuracy: 0.9790  
Epoch 33/100  
7/7 [=====] - 0s 10ms/step - loss: 0.2111 - accuracy: 0.9343 - val_loss: 0.1558 - val_accuracy: 0.9720  
Epoch 34/100  
7/7 [=====] - 0s 7ms/step - loss: 0.2042 - accuracy: 0.9390 - val_loss: 0.1552 - val_accuracy: 0.9650  
Epoch 35/100  
7/7 [=====] - 0s 10ms/step - loss: 0.2014 - accuracy: 0.9390 - val_loss: 0.1543 - val_accuracy: 0.9720  
Epoch 36/100  
7/7 [=====] - 0s 8ms/step - loss: 0.1990 - accuracy: 0.9296 - val_loss: 0.1533 - val_accuracy: 0.9720  
Epoch 37/100  
7/7 [=====] - 0s 7ms/step - loss: 0.1989 - accuracy: 0.9296 - val_loss: 0.1527 - val_accuracy: 0.9720  
Epoch 38/100  
7/7 [=====] - 0s 7ms/step - loss: 0.2030 - accuracy: 0.9343 - val_loss: 0.1505 - val_accuracy: 0.9720
```

This code snippet orchestrates the training phase of a machine learning model, particularly a neural network, by defining various parameters crucial for the training process. These parameters include the choice of loss function for assessing training data, the verbosity level for output display (set to 1 for detailed progress display), the number of epochs (set to 100 for full dataset traversal), and the batch size (set to 64 for processing efficiency). Additionally, it designates validation data to evaluate model performance during training. Upon execution, the `model.fit()` function undertakes the training process, updating model parameters iteratively based on the defined parameters, while generating a history object containing vital training metrics for analysis and evaluation.

Throughout the 100 epochs of model training, a discernible trend emerges wherein the **loss metric steadily decreases**, indicative of the model's increasing ability to minimize prediction errors on the training dataset. Simultaneously, the **accuracy metric demonstrates improvement**, reflecting the model's enhanced capacity to make correct predictions. Moreover, the **validation loss diminishes progressively**, suggesting the generalization capability of the model on unseen data improves over epochs. This is **mirrored by the validation accuracy metric, which showcases an upward trajectory**, signifying the model's ability to generalize well to new data samples. These phenomena can be attributed to the iterative optimization process employed during training, wherein the model updates its internal parameters iteratively to minimize the defined loss function. As epochs progress, the model learns intricate patterns within the data, leading to refined predictions and improved generalization performance, thus exemplifying the iterative nature of machine learning model training and optimization.

In the next part, we will showcase the upward and downward trends of these 4 crucial parameters by plotting them into 2 separate plots in a 2D space, one that will show the loss during epochs and the other displaying the accuracy over epochs.

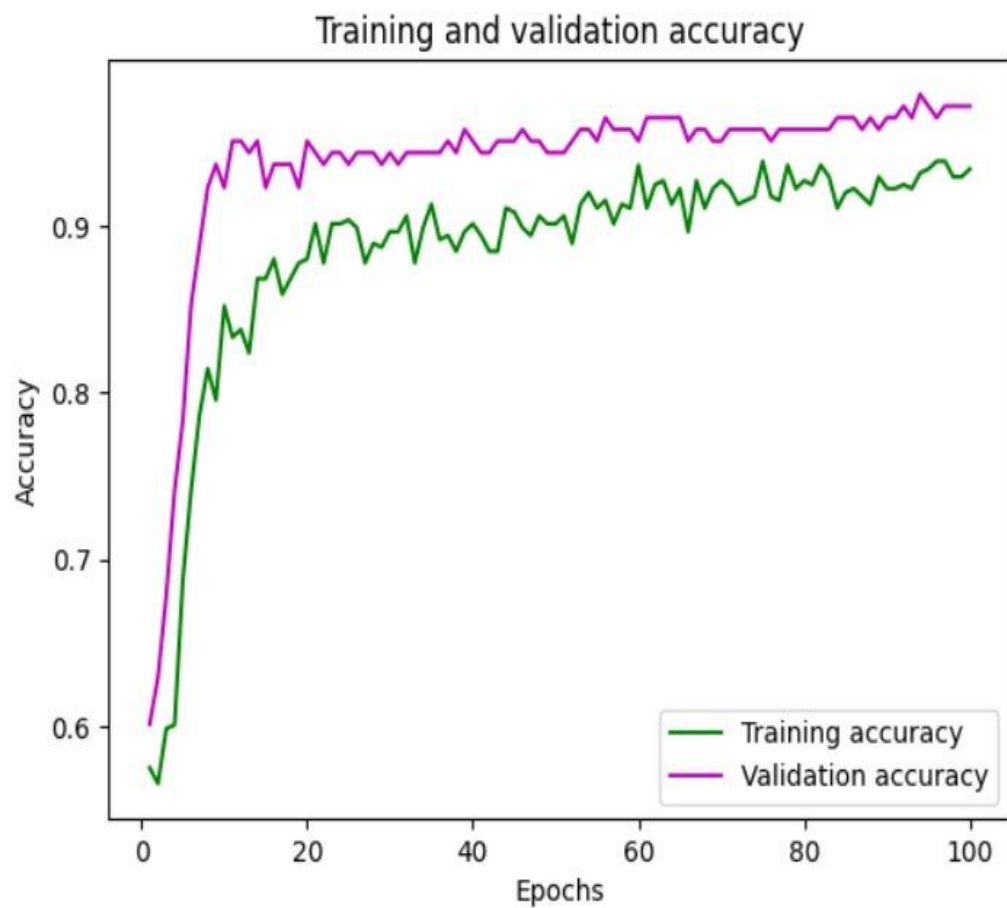
```
1 usage
62 def plot_loss(history):
63     loss = history.history['loss']
64     val_loss = history.history['val_loss']
65     epochs = range(1, len(loss) + 1)
66     plt.plot(*args: epochs, loss, 'g', label='Training loss')
67     plt.plot(*args: epochs, val_loss, 'm', label='Validation loss')
68     plt.title('Training and validation loss')
69     plt.xlabel('Epochs')
70     plt.ylabel('Loss')
71     plt.legend()
72     plt.show()
73
74
```




```

1 usage
75 def plot_accuracy(history):
76     accuracy = history.history['accuracy']
77     val_accuracy = history.history['val_accuracy']
78     epochs = range(1, len(accracy) + 1)
79     plt.plot(*args: epochs, accuracy, 'g', label='Training accuracy')
80     plt.plot(*args: epochs, val_accuracy, 'm', label='Validation accuracy')
81     plt.title('Training and validation accuracy')
82     plt.xlabel('Epochs')
83     plt.ylabel('Accuracy')
84     plt.legend()
85     plt.show()
86

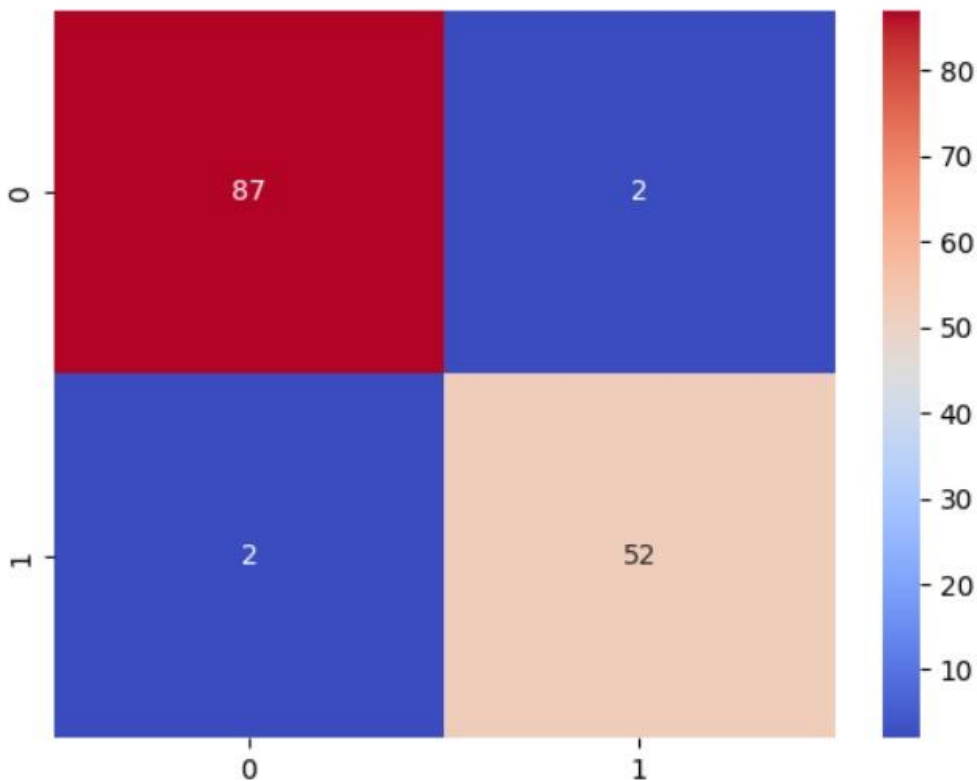
```



3.4 Model Evaluation

```
1 usage
88 def evaluate_model(model, X_test, y_test):
89     y_pred = model.predict(X_test)
90     y_pred = (y_pred > 0.5)
91     confusion_matr = confusion_matrix(y_test, y_pred)
92     color_palette = sns.color_palette(palette="coolwarm", as_cmap=True)
93     sns.heatmap(confusion_matr, annot=True, cmap=color_palette)
94     plt.show()
95
96
```

5/5 [=====] - 0s 3ms/step
<Axes: >



This code predicts binary outcomes from test data using a pre-trained model and transforms them into binary predictions. Then, it computes a confusion matrix to evaluate the model's classification performance. Finally, it visualizes the confusion matrix as a heatmap using Seaborn, with color palettes ranging from cool to warm tones for clear interpretation.

4. Testing and Parameter Optimization

This chapter of the thesis focuses on evaluating the performance of this deep learning model and optimizing its parameters to enhance its effectiveness. This critical phase involves fine-tuning various aspects of the model architecture and training process to achieve the best possible results (accuracy-wise and loss-wise).

4.1 Experiments with different numbers of hidden layers and neurons

Experiment:

Model 1(Original)

VS

Model 2

Input layer: 32 neurons

Input layer: 32 neurons

Hidden layer 1: 16 neurons

Hidden layer: 64 neurons

Output layer: 1 neuron

Hidden layer: 64 neurons

Hidden layer 1: 32 neurons

Output layer 1: 1 neuron

Model 2 code:

```
def build_model():
    model = Sequential()
    model.add(Dense(units=32, input_dim=30, activation='relu')) # Input layer with 32 neurons
    model.add(Dropout(0.2))
    model.add(Dense(units=64, activation='relu')) # Hidden layer with 64 neurons
    model.add(Dense(units=64, activation='relu')) # Additional hidden layer with 64 neurons
    model.add(Dense(units=32, activation='relu')) # Additional hidden layer with 32 neurons
    model.add(Dense(units=1, activation='sigmoid')) # Output layer with 1 neuron (binary classification)
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
    print(model.summary())
    return model
```

Results:

4.1.1 Parameters trained

Model 1(Original):

Model: "sequential_1"		
Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 16)	512
dropout (Dropout)	(None, 16)	0
dense_2 (Dense)	(None, 1)	17
activation (Activation)	(None, 1)	0
Total params: 529 (2.07 KB)		
Trainable params: 529 (2.07 KB)		
Non-trainable params: 0 (0.00 Byte)		
None		

Model 2:

Model: "sequential_1"		
Layer (type)	Output Shape	Param #
dense_5 (Dense)	(None, 32)	992
dropout_1 (Dropout)	(None, 32)	0
dense_6 (Dense)	(None, 64)	2112
dense_7 (Dense)	(None, 64)	4160
dense_8 (Dense)	(None, 32)	2080
dense_9 (Dense)	(None, 1)	33
Total params: 9377 (36.63 KB)		
Trainable params: 9377 (36.63 KB)		
Non-trainable params: 0 (0.00 Byte)		
None		

As seen in the data above, the first model comprises a single hidden layer with 512 trainable parameters, offering a relatively straightforward architecture. In contrast, the updated model incorporates additional layers, totaling 2112 parameters in the first layer, 4160 in the second, and 2080 in the third. This augmentation leads to a more intricate neural network, capable of capturing complex data relationships and patterns. With increased depth and capacity, the enhanced model can perform more nuanced feature extraction, learning hierarchical representations for improved performance and generalization.

4.1.2 Epochs accuracy and loss values

Model 1(Original):

```
Epoch 88/100 - 0s 7ms/step - loss: 0.2319 - accuracy: 0.9178 - val_loss: 0.1684 - val_accuracy: 0.9580
Epoch 89/100 - 0s 11ms/step - loss: 0.2210 - accuracy: 0.9131 - val_loss: 0.1665 - val_accuracy: 0.9650
Epoch 90/100 - 0s 9ms/step - loss: 0.2200 - accuracy: 0.9296 - val_loss: 0.1654 - val_accuracy: 0.9580
Epoch 91/100 - 0s 8ms/step - loss: 0.2253 - accuracy: 0.9225 - val_loss: 0.1643 - val_accuracy: 0.9650
Epoch 92/100 - 0s 8ms/step - loss: 0.2205 - accuracy: 0.9225 - val_loss: 0.1631 - val_accuracy: 0.9650
Epoch 93/100 - 0s 8ms/step - loss: 0.2281 - accuracy: 0.9249 - val_loss: 0.1617 - val_accuracy: 0.9720
Epoch 94/100 - 0s 8ms/step - loss: 0.2113 - accuracy: 0.9225 - val_loss: 0.1595 - val_accuracy: 0.9650
Epoch 95/100 - 0s 10ms/step - loss: 0.2108 - accuracy: 0.9319 - val_loss: 0.1569 - val_accuracy: 0.9790
Epoch 96/100 - 0s 10ms/step - loss: 0.2111 - accuracy: 0.9343 - val_loss: 0.1558 - val_accuracy: 0.9720
Epoch 97/100 - 0s 7ms/step - loss: 0.2042 - accuracy: 0.9390 - val_loss: 0.1552 - val_accuracy: 0.9650
Epoch 98/100 - 0s 10ms/step - loss: 0.2014 - accuracy: 0.9390 - val_loss: 0.1543 - val_accuracy: 0.9720
Epoch 99/100 - 0s 8ms/step - loss: 0.1990 - accuracy: 0.9296 - val_loss: 0.1533 - val_accuracy: 0.9720
Epoch 100/100 - 0s 7ms/step - loss: 0.1989 - accuracy: 0.9296 - val_loss: 0.1527 - val_accuracy: 0.9720
```

Model 2:

```
Epoch 84/100 - 0s 15ms/step - loss: 0.0523 - accuracy: 0.9789 - val_loss: 0.0648 - val_accuracy: 0.9650
Epoch 85/100 - 0s 16ms/step - loss: 0.0564 - accuracy: 0.9812 - val_loss: 0.0887 - val_accuracy: 0.9650
Epoch 86/100 - 0s 14ms/step - loss: 0.0427 - accuracy: 0.9883 - val_loss: 0.0823 - val_accuracy: 0.9650
Epoch 87/100 - 0s 52ms/step - loss: 0.0383 - accuracy: 0.9859 - val_loss: 0.0808 - val_accuracy: 0.9650
Epoch 88/100 - 0s 33ms/step - loss: 0.0498 - accuracy: 0.9859 - val_loss: 0.0880 - val_accuracy: 0.9650
Epoch 89/100 - 0s 31ms/step - loss: 0.0477 - accuracy: 0.9812 - val_loss: 0.0709 - val_accuracy: 0.9720
Epoch 90/100 - 0s 24ms/step - loss: 0.0435 - accuracy: 0.9765 - val_loss: 0.0702 - val_accuracy: 0.9790
Epoch 91/100 - 0s 38ms/step - loss: 0.0377 - accuracy: 0.9883 - val_loss: 0.0629 - val_accuracy: 0.9790
Epoch 92/100 - 0s 29ms/step - loss: 0.0524 - accuracy: 0.9812 - val_loss: 0.0797 - val_accuracy: 0.9720
Epoch 93/100 - 0s 14ms/step - loss: 0.0298 - accuracy: 0.9859 - val_loss: 0.0608 - val_accuracy: 0.9790
Epoch 94/100 - 0s 16ms/step - loss: 0.0401 - accuracy: 0.9812 - val_loss: 0.0881 - val_accuracy: 0.9650
Epoch 95/100 - 0s 16ms/step - loss: 0.0341 - accuracy: 0.9859 - val_loss: 0.0716 - val_accuracy: 0.9790
Epoch 96/100 - 0s 17ms/step - loss: 0.0372 - accuracy: 0.9906 - val_loss: 0.0917 - val_accuracy: 0.9650
Epoch 97/100 - 0s 18ms/step - loss: 0.0374 - accuracy: 0.9859 - val_loss: 0.0835 - val_accuracy: 0.9720
Epoch 98/100 - 0s 16ms/step - loss: 0.0355 - accuracy: 0.9859 - val_loss: 0.0761 - val_accuracy: 0.9720
Epoch 99/100 - 0s 16ms/step - loss: 0.0365 - accuracy: 0.9836 - val_loss: 0.0829 - val_accuracy: 0.9720
Epoch 100/100 - 0s 16ms/step - loss: 0.0354 - accuracy: 0.9883 - val_loss: 0.0633 - val_accuracy: 0.9790
```

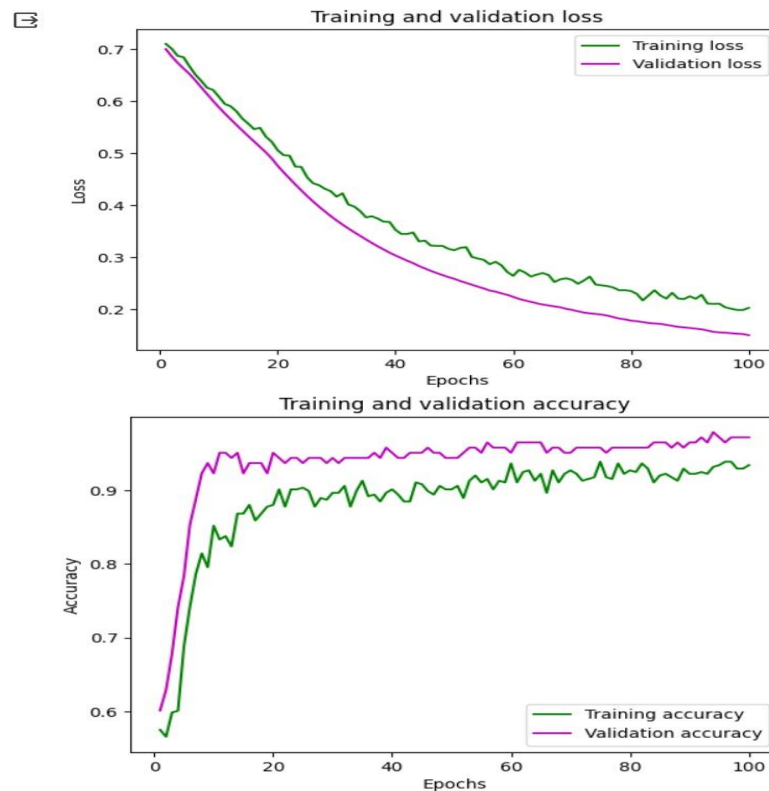
The comparison between the epochs of the two models reveals notable differences in performance. The first model, characterized by a simpler architecture with one input layer of 32 neurons and one hidden layer of 16 neurons, achieved moderate results in its last epoch. It attained a loss of 0.2, an accuracy of 0.9343, a validation loss of 0.15, and a validation accuracy of

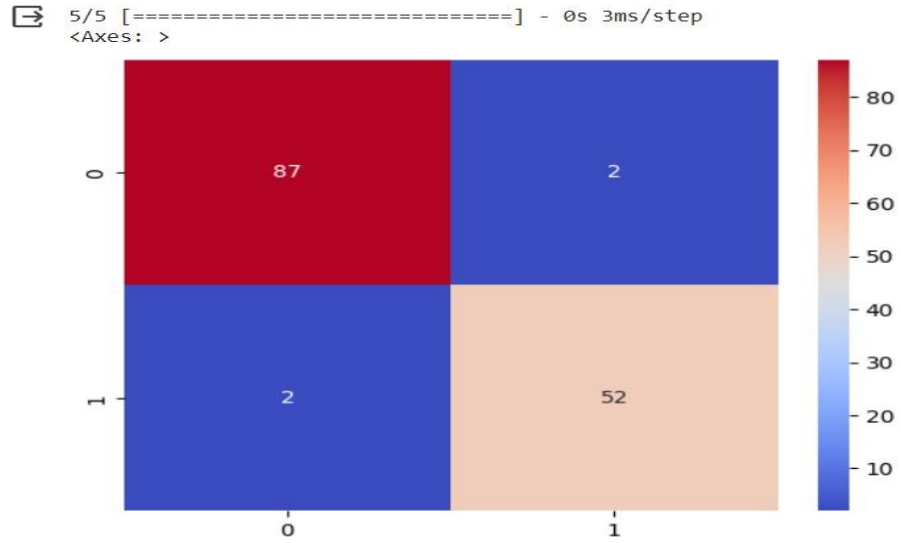
0.9720. In contrast, the second model, featuring a more complex architecture with one input layer of 32 neurons, three hidden layers (64, 64, and 32 neurons respectively), and an output layer of 1 neuron, exhibited superior performance. Its final epoch showcased a **loss of 0.03**, an **accuracy of 0.9883**, a **validation loss of 0.063**, and a **validation accuracy of 0.9790**.

Despite the second model's longer computation time per epoch, approximately double that of the first model, the additional computational overhead is justified by its significantly improved performance metrics. With a relatively short computation time of around 16 milliseconds per step, the second model offers a compelling trade-off between computational complexity and performance gains, making it a preferable choice for breast cancer detection tasks.

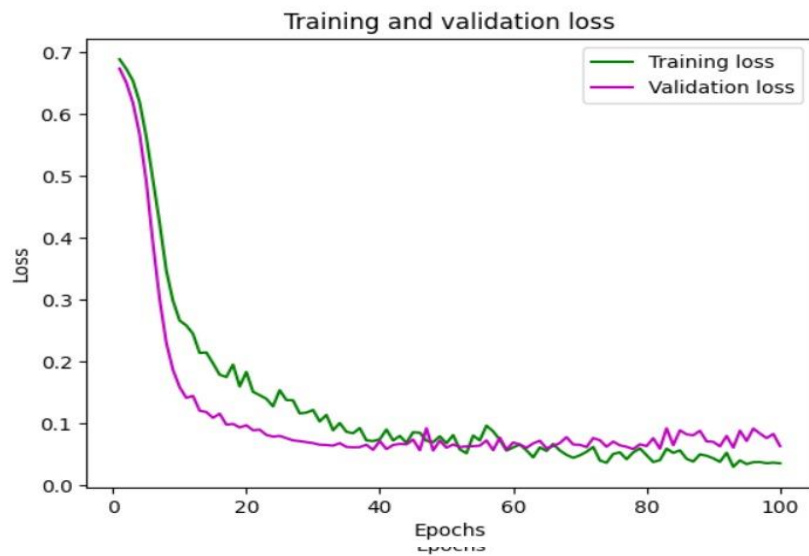
4.1.3 Plot comparisons

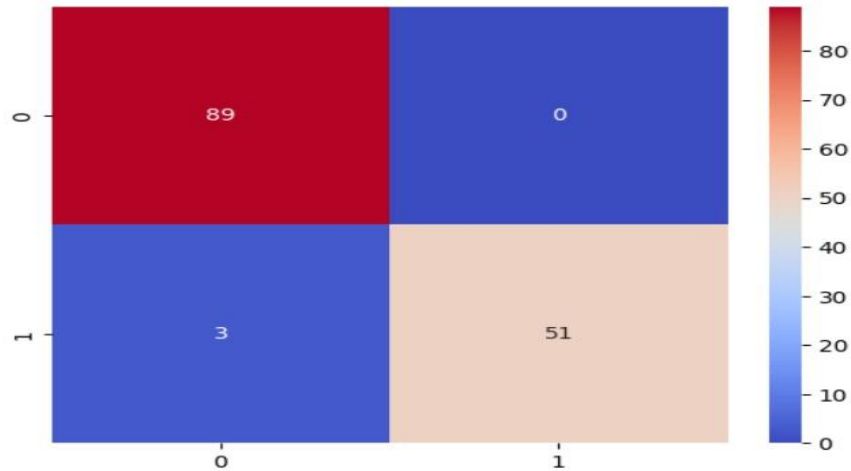
Model 1(Original):





Model 2:





As evident from the plots depicting the loss and accuracy over epochs, the second model consistently outperforms the first model. The second model exhibits a faster convergence to lower loss values and higher accuracy rates compared to the first model. This accelerated convergence suggests that the more complex architecture of the second model enables it to learn and adapt more effectively to the underlying patterns in the data.

Furthermore, upon visualizing the confusion matrix heatmap, it becomes apparent that the second model yields superior performance metrics. The heatmap illustrates clearer distinctions between true positive and true negative classifications, indicative of the second model's enhanced ability to correctly identify instances of breast cancer. Overall, the combination of faster convergence and improved classification accuracy underscores the effectiveness of the second model in breast cancer detection tasks.

4.2 Experiments with different activation functions

In this next part, we will choose the most efficient model from our first experiment(4.1) and compare it to another one.

Experiment:

Model 2:

Input layer: 32 n, Activation:'relu'
 Hidden layer: 64 n, Activation:'relu'
 Hidden layer: 64 n, Activation:'relu'

vs

Model 3

Input layer: 32 n, Activation:'tanh'
 Hidden layer: 64 n, Activation:'LeakyRelu'
 Hidden layer: 64 n, Activation:'LeakyRelu'

Hidden layer: 32 n, Activation:'LeakyRelu'

Output layer: 1 n, Activation:'sigmoid'

Abbreviation used: 'n'='neurons'.

Model 3:

```
from keras.layers import LeakyReLU
from keras.activations import tanh
usage

def build_model():
    # Defining the model
    model = Sequential()
    model.add(Dense(units=32, input_dim=30, activation='tanh')) # Input layer with 32 neurons and 'tanh' a
    model.add(Dropout(0.2))
    model.add(Dense(units=64, activation=LeakyReLU(alpha=0.1))) # Hidden layer with 64 neurons and LeakyRe
    model.add(Dense(units=64, activation=LeakyReLU(alpha=0.1))) # Additional hidden layer with 64 neurons
    model.add(Dense(units=32, activation=LeakyReLU(alpha=0.1))) # Additional hidden layer with 32 neurons
    model.add(Dense(units=1, activation='sigmoid')) # Output layer with 1 neuron (binary classification)
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
    print(model.summary())
```

4.2.1 Parameters trained

```
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
dense_5 (Dense)	(None, 32)	992
dropout_1 (Dropout)	(None, 32)	0
dense_6 (Dense)	(None, 64)	2112
dense_7 (Dense)	(None, 64)	4160
dense_8 (Dense)	(None, 32)	2080
dense_9 (Dense)	(None, 1)	33

```
-----
Total params: 9377 (36.63 KB)
Trainable params: 9377 (36.63 KB)
Non-trainable params: 0 (0.00 Byte)
```

```
None
Model: "sequential_4"
```

Layer (type)	Output Shape	Param #
dense_16 (Dense)	(None, 32)	992
dropout_4 (Dropout)	(None, 32)	0
dense_17 (Dense)	(None, 64)	2112
dense_18 (Dense)	(None, 64)	4160
dense_19 (Dense)	(None, 32)	2080
dense_20 (Dense)	(None, 1)	33

```
=====
Total params: 9377 (36.63 KB)
Trainable params: 9377 (36.63 KB)
Non-trainable params: 0 (0.00 Byte)
```

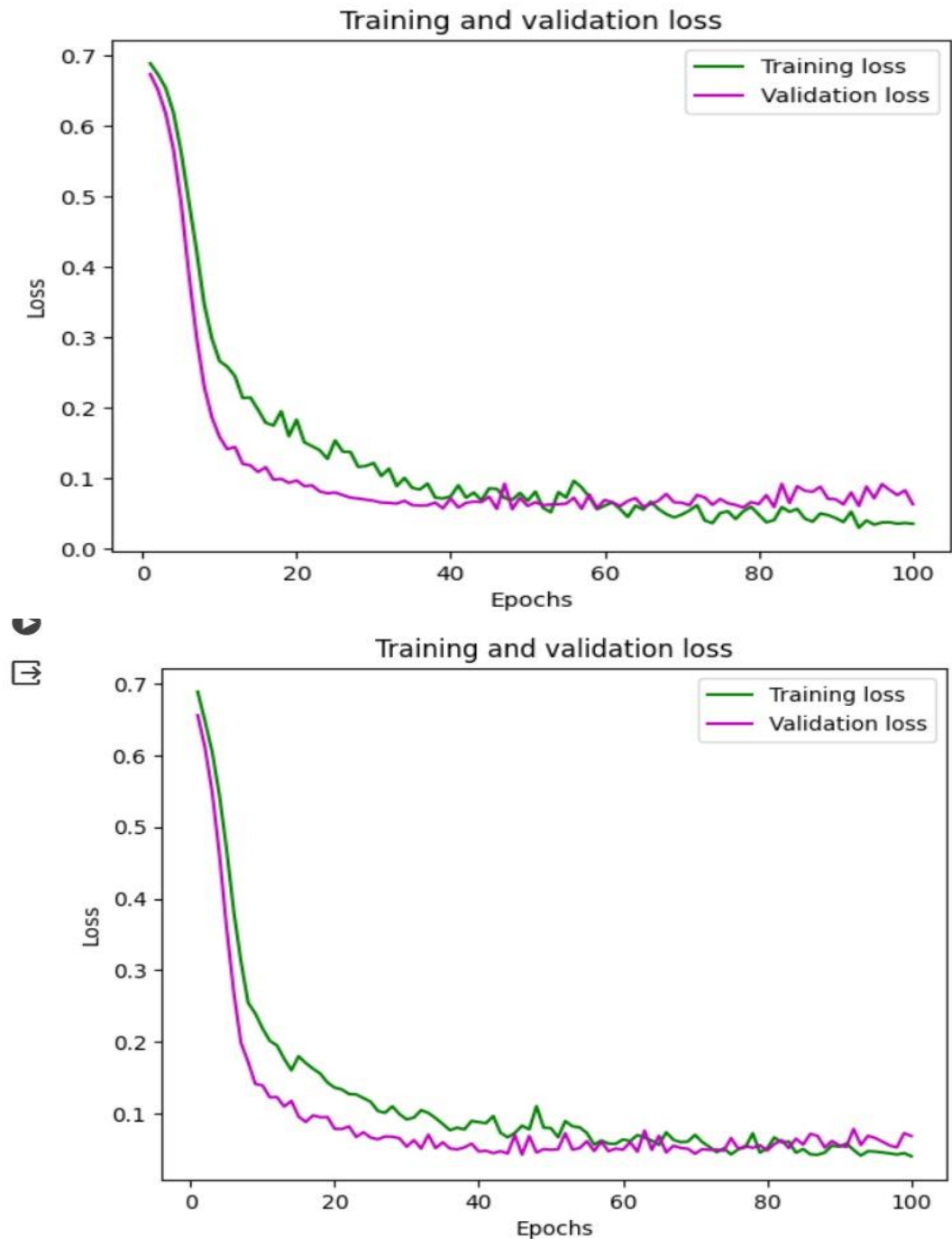
In both models, despite having slightly different architectures, the number of trainable parameters remains the same at 9377. This similarity in parameter count suggests that both models have comparable complexity and capacity to learn from the data. Despite their architectural differences regarding activation functions, their capacity to capture and represent features in the data remains consistent, allowing for fair comparison in terms of model performance and generalization.

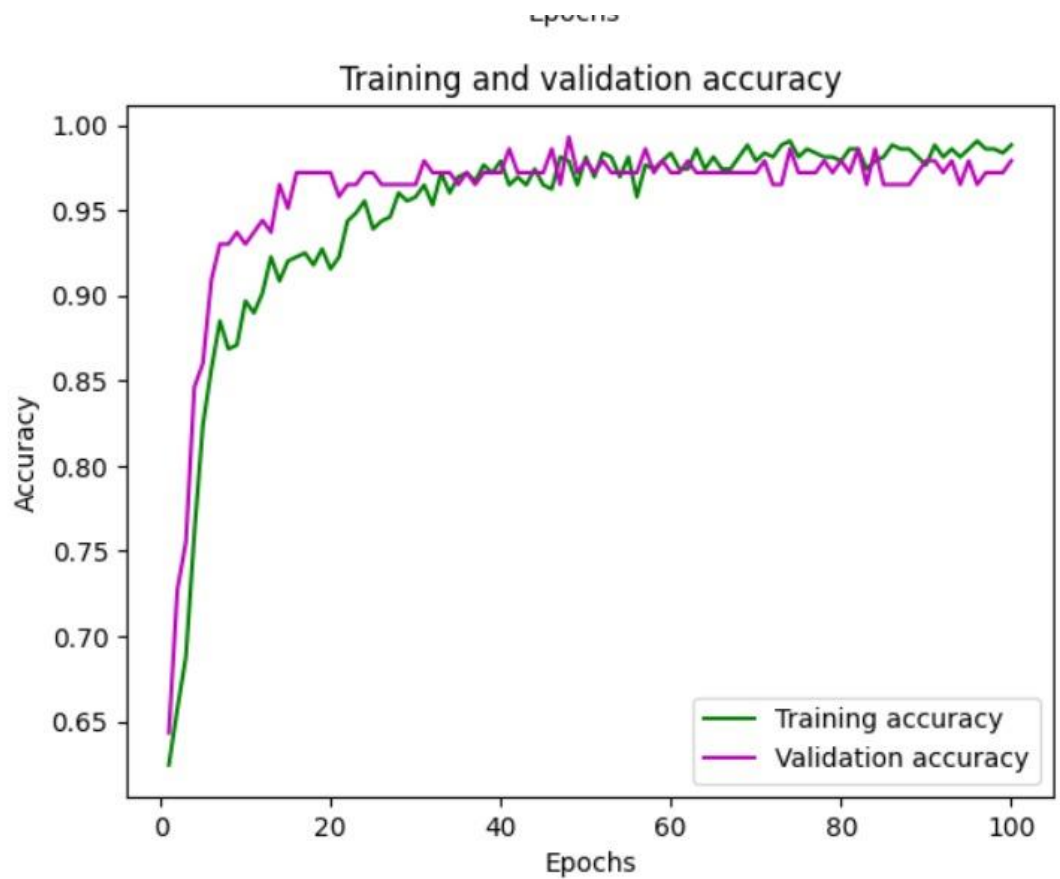
4.2.2 Epochs accuracy and loss values

Epoch 84/100	7/7 [=====]	- 0s 15ms/step	- loss: 0.0523	- accuracy: 0.9789	- val_loss: 0.0648	- val_
Epoch 85/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0564	- accuracy: 0.9812	- val_loss: 0.0887	- val_accuracy: 0.9650
Epoch 86/100	7/7 [=====]	- 0s 14ms/step	- loss: 0.0427	- accuracy: 0.9883	- val_loss: 0.0823	- val_accuracy: 0.9650
Epoch 87/100	7/7 [=====]	- 0s 52ms/step	- loss: 0.0383	- accuracy: 0.9859	- val_loss: 0.0808	- val_accuracy: 0.9650
Epoch 88/100	7/7 [=====]	- 0s 33ms/step	- loss: 0.0498	- accuracy: 0.9859	- val_loss: 0.0880	- val_accuracy: 0.9650
Epoch 89/100	7/7 [=====]	- 0s 31ms/step	- loss: 0.0477	- accuracy: 0.9812	- val_loss: 0.0709	- val_accuracy: 0.9720
Epoch 90/100	7/7 [=====]	- 0s 24ms/step	- loss: 0.0435	- accuracy: 0.9765	- val_loss: 0.0702	- val_accuracy: 0.9790
Epoch 91/100	7/7 [=====]	- 0s 38ms/step	- loss: 0.0377	- accuracy: 0.9883	- val_loss: 0.0629	- val_accuracy: 0.9790
Epoch 92/100	7/7 [=====]	- 0s 29ms/step	- loss: 0.0524	- accuracy: 0.9812	- val_loss: 0.0797	- val_accuracy: 0.9720
Epoch 93/100	7/7 [=====]	- 0s 14ms/step	- loss: 0.0298	- accuracy: 0.9859	- val_loss: 0.0608	- val_accuracy: 0.9790
Epoch 94/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0401	- accuracy: 0.9812	- val_loss: 0.0881	- val_accuracy: 0.9650
Epoch 95/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0341	- accuracy: 0.9859	- val_loss: 0.0716	- val_accuracy: 0.9790
Epoch 96/100	7/7 [=====]	- 0s 17ms/step	- loss: 0.0372	- accuracy: 0.9906	- val_loss: 0.0917	- val_accuracy: 0.9650
Epoch 97/100	7/7 [=====]	- 0s 18ms/step	- loss: 0.0374	- accuracy: 0.9859	- val_loss: 0.0835	- val_accuracy: 0.9720
Epoch 98/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0355	- accuracy: 0.9859	- val_loss: 0.0761	- val_accuracy: 0.9720
Epoch 99/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0365	- accuracy: 0.9836	- val_loss: 0.0829	- val_accuracy: 0.9720
Epoch 100/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0354	- accuracy: 0.9883	- val_loss: 0.0633	- val_accuracy: 0.9790
Epoch 85/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0505	- accuracy: 0.9859	- val_loss: 0.0566	- val_accuracy: 0.9790
Epoch 86/100	7/7 [=====]	- 0s 13ms/step	- loss: 0.0431	- accuracy: 0.9859	- val_loss: 0.0717	- val_accuracy: 0.9650
Epoch 87/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0425	- accuracy: 0.9859	- val_loss: 0.0688	- val_accuracy: 0.9650
Epoch 88/100	7/7 [=====]	- 0s 14ms/step	- loss: 0.0456	- accuracy: 0.9859	- val_loss: 0.0526	- val_accuracy: 0.9860
Epoch 89/100	7/7 [=====]	- 0s 8ms/step	- loss: 0.0553	- accuracy: 0.9836	- val_loss: 0.0617	- val_accuracy: 0.9650
Epoch 90/100	7/7 [=====]	- 0s 10ms/step	- loss: 0.0538	- accuracy: 0.9812	- val_loss: 0.0557	- val_accuracy: 0.9860
Epoch 91/100	7/7 [=====]	- 0s 10ms/step	- loss: 0.0582	- accuracy: 0.9812	- val_loss: 0.0535	- val_accuracy: 0.9860
Epoch 92/100	7/7 [=====]	- 0s 23ms/step	- loss: 0.0492	- accuracy: 0.9812	- val_loss: 0.0786	- val_accuracy: 0.9650
Epoch 93/100	7/7 [=====]	- 0s 11ms/step	- loss: 0.0413	- accuracy: 0.9836	- val_loss: 0.0562	- val_accuracy: 0.9860
Epoch 94/100	7/7 [=====]	- 0s 8ms/step	- loss: 0.0475	- accuracy: 0.9859	- val_loss: 0.0690	- val_accuracy: 0.9650
Epoch 95/100	7/7 [=====]	- 0s 8ms/step	- loss: 0.0469	- accuracy: 0.9859	- val_loss: 0.0659	- val_accuracy: 0.9720
Epoch 96/100	7/7 [=====]	- 0s 10ms/step	- loss: 0.0456	- accuracy: 0.9789	- val_loss: 0.0608	- val_accuracy: 0.9720
Epoch 97/100	7/7 [=====]	- 0s 10ms/step	- loss: 0.0444	- accuracy: 0.9812	- val_loss: 0.0555	- val_accuracy: 0.9860
Epoch 98/100	7/7 [=====]	- 0s 11ms/step	- loss: 0.0428	- accuracy: 0.9859	- val_loss: 0.0528	- val_accuracy: 0.9860
Epoch 99/100	7/7 [=====]	- 0s 8ms/step	- loss: 0.0448	- accuracy: 0.9883	- val_loss: 0.0726	- val_accuracy: 0.9650
Epoch 100/100	7/7 [=====]	- 0s 8ms/step	- loss: 0.0404	- accuracy: 0.9836	- val_loss: 0.0686	- val_accuracy: 0.9650

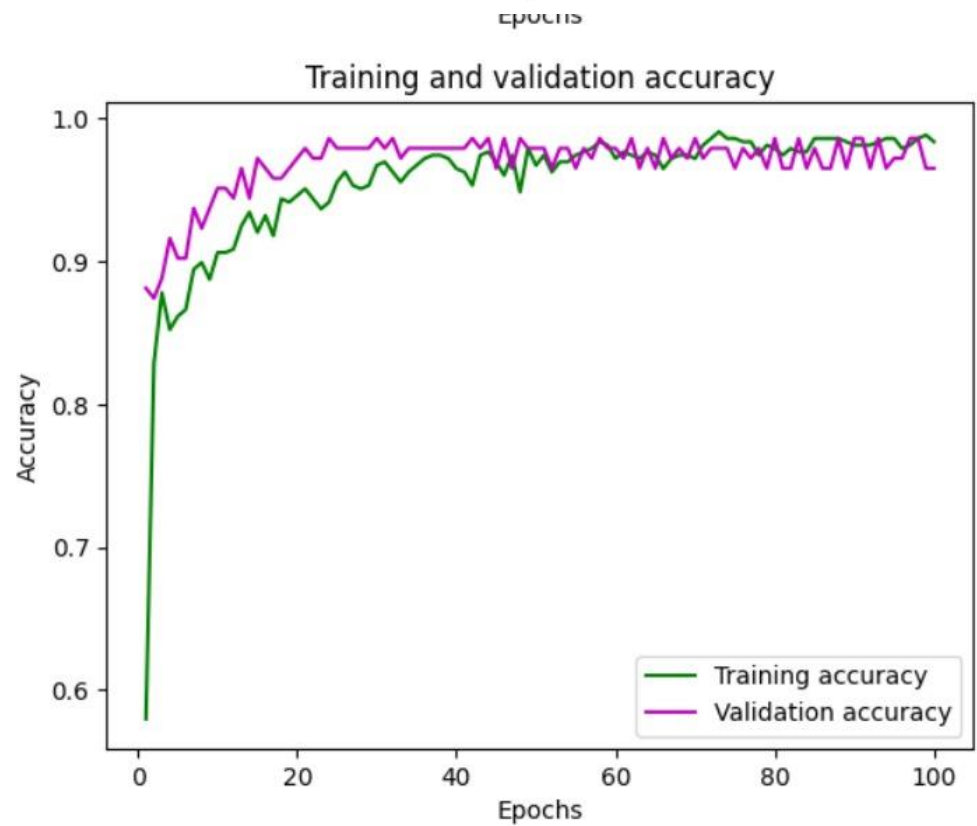
During the 100 epochs of testing, both models exhibited similar trends in accuracy and loss values, with a maximum accuracy of 0.9883 achieved by both. However, the second model attained this peak accuracy faster, reaching it within 9 seconds of computation, compared to the third model, which took 21 seconds. This highlights the efficiency of the second model in terms of convergence speed, despite the similar final performance achieved by both models.

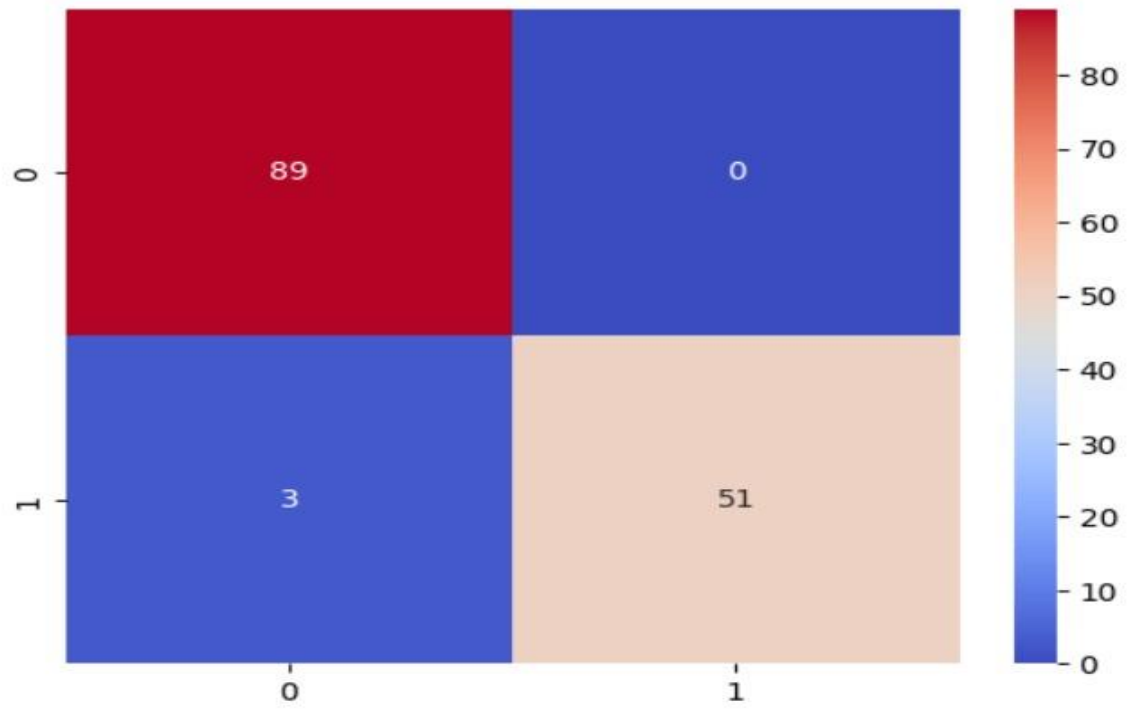
4.2.3 Plot comparisons



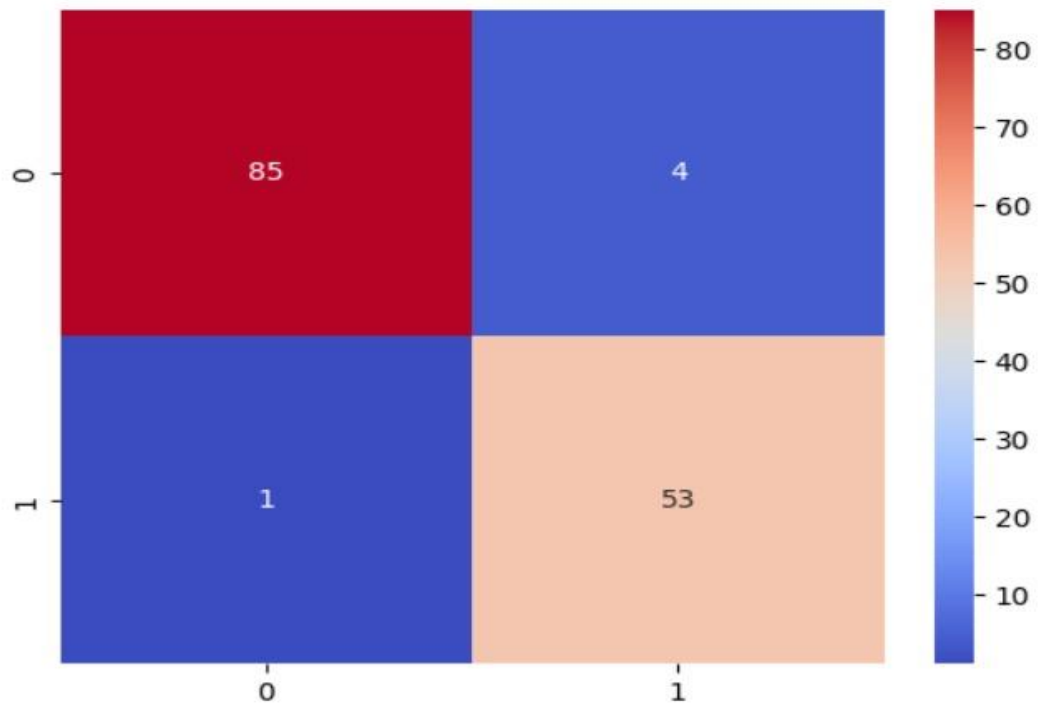


↳





5/5 [=====] - 0s 2ms/step
<Axes: >



Both models exhibit similar trends in both training and validation accuracy as well as training and validation loss, along with comparable values in the confusion matrix heatmap. Consequently, they appear to perform similarly in terms of classification performance. However, the second model stands out due to its shorter computation time, achieving similar peak accuracy and loss values within a significantly shorter duration. Therefore, while both models demonstrate comparable efficacy, the second model's efficiency makes it the preferred choice for this task.

4.3 Experiments with different values for epochs and batch_size

For this part, we will only change the values of epochs and batch_size in our model training function(train_model) and use the same architecture as the one for Model 2 presented above. We will also only compare the values of the last epochs regarding the accuracy and loss.

Train Model 1:

Epochs:100, batch_size:64

Train Model 2:

Epochs:150, batch_size: 32

Epoch 84/100	7/7 [=====]	- 0s 15ms/step	- loss: 0.0523	- accuracy: 0.9789	- val_loss: 0.0648	- val	↑ ↓ ↻ 📄 ⚙
Epoch 85/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0564	- accuracy: 0.9812	- val_loss: 0.0887	- val_accuracy: 0.9650	
Epoch 86/100	7/7 [=====]	- 0s 14ms/step	- loss: 0.0427	- accuracy: 0.9883	- val_loss: 0.0823	- val_accuracy: 0.9650	
Epoch 87/100	7/7 [=====]	- 0s 52ms/step	- loss: 0.0383	- accuracy: 0.9859	- val_loss: 0.0808	- val_accuracy: 0.9650	
Epoch 88/100	7/7 [=====]	- 0s 33ms/step	- loss: 0.0498	- accuracy: 0.9859	- val_loss: 0.0880	- val_accuracy: 0.9650	
Epoch 89/100	7/7 [=====]	- 0s 31ms/step	- loss: 0.0477	- accuracy: 0.9812	- val_loss: 0.0709	- val_accuracy: 0.9720	
Epoch 90/100	7/7 [=====]	- 0s 24ms/step	- loss: 0.0435	- accuracy: 0.9765	- val_loss: 0.0702	- val_accuracy: 0.9790	
Epoch 91/100	7/7 [=====]	- 0s 38ms/step	- loss: 0.0377	- accuracy: 0.9883	- val_loss: 0.0629	- val_accuracy: 0.9790	
Epoch 92/100	7/7 [=====]	- 0s 29ms/step	- loss: 0.0524	- accuracy: 0.9812	- val_loss: 0.0797	- val_accuracy: 0.9720	
Epoch 93/100	7/7 [=====]	- 0s 14ms/step	- loss: 0.0298	- accuracy: 0.9859	- val_loss: 0.0608	- val_accuracy: 0.9790	
Epoch 94/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0401	- accuracy: 0.9812	- val_loss: 0.0881	- val_accuracy: 0.9650	
Epoch 95/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0341	- accuracy: 0.9859	- val_loss: 0.0716	- val_accuracy: 0.9790	
Epoch 96/100	7/7 [=====]	- 0s 17ms/step	- loss: 0.0372	- accuracy: 0.9906	- val_loss: 0.0917	- val_accuracy: 0.9650	
Epoch 97/100	7/7 [=====]	- 0s 18ms/step	- loss: 0.0374	- accuracy: 0.9859	- val_loss: 0.0835	- val_accuracy: 0.9720	
Epoch 98/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0355	- accuracy: 0.9859	- val_loss: 0.0761	- val_accuracy: 0.9720	
Epoch 99/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0365	- accuracy: 0.9836	- val_loss: 0.0829	- val_accuracy: 0.9720	
Epoch 100/100	7/7 [=====]	- 0s 16ms/step	- loss: 0.0354	- accuracy: 0.9883	- val_loss: 0.0633	- val_accuracy: 0.9790	
14/14 [=====]	14/14 [=====]	- 0s 7ms/step	- loss: 0.0413	- accuracy: 0.9836	- val_loss: 0.1107	- val	↑ ↓ ↻ 📄 ⚙ 🖨
Epoch 135/150	14/14 [=====]	- 0s 6ms/step	- loss: 0.0228	- accuracy: 0.9906	- val_loss: 0.0955	- val_accuracy: 0.9650	
Epoch 136/150	14/14 [=====]	- 0s 7ms/step	- loss: 0.0190	- accuracy: 0.9883	- val_loss: 0.1022	- val_accuracy: 0.9650	
Epoch 137/150	14/14 [=====]	- 0s 7ms/step	- loss: 0.0198	- accuracy: 0.9906	- val_loss: 0.1148	- val_accuracy: 0.9650	
Epoch 138/150	14/14 [=====]	- 0s 8ms/step	- loss: 0.0185	- accuracy: 0.9953	- val_loss: 0.1034	- val_accuracy: 0.9790	
Epoch 139/150	14/14 [=====]	- 0s 6ms/step	- loss: 0.0250	- accuracy: 0.9836	- val_loss: 0.1495	- val_accuracy: 0.9510	
Epoch 140/150	14/14 [=====]	- 0s 6ms/step	- loss: 0.0155	- accuracy: 0.9953	- val_loss: 0.1174	- val_accuracy: 0.9650	
Epoch 141/150	14/14 [=====]	- 0s 7ms/step	- loss: 0.0164	- accuracy: 0.9930	- val_loss: 0.1202	- val_accuracy: 0.9650	
Epoch 142/150	14/14 [=====]	- 0s 8ms/step	- loss: 0.0084	- accuracy: 1.0000	- val_loss: 0.1089	- val_accuracy: 0.9650	
Epoch 143/150	14/14 [=====]	- 0s 7ms/step	- loss: 0.0078	- accuracy: 0.9977	- val_loss: 0.1127	- val_accuracy: 0.9650	
Epoch 144/150	14/14 [=====]	- 0s 7ms/step	- loss: 0.0121	- accuracy: 0.9953	- val_loss: 0.1116	- val_accuracy: 0.9650	
Epoch 145/150	14/14 [=====]	- 0s 6ms/step	- loss: 0.0127	- accuracy: 0.9977	- val_loss: 0.1332	- val_accuracy: 0.9580	
Epoch 146/150	14/14 [=====]	- 0s 7ms/step	- loss: 0.0204	- accuracy: 0.9883	- val_loss: 0.1367	- val_accuracy: 0.9650	
Epoch 147/150	14/14 [=====]	- 0s 7ms/step	- loss: 0.0168	- accuracy: 0.9906	- val_loss: 0.1560	- val_accuracy: 0.9580	
Epoch 148/150	14/14 [=====]	- 0s 7ms/step	- loss: 0.0231	- accuracy: 0.9906	- val_loss: 0.1148	- val_accuracy: 0.9720	
Epoch 149/150	14/14 [=====]	- 0s 6ms/step	- loss: 0.0223	- accuracy: 0.9906	- val_loss: 0.1260	- val_accuracy: 0.9720	
Epoch 150/150	14/14 [=====]	- 0s 7ms/step	- loss: 0.0191	- accuracy: 0.9930	- val_loss: 0.1191	- val_accuracy: 0.9720	

In comparing the two training functions, it's evident that the second one, with 150 epochs and a batch size of 32, achieves remarkable results. It achieves near-perfect accuracy values of 1.0, 0.9977, and 0.9930 across different epochs, accompanied by exceptionally low losses of around 0.01 and a final value of 0.0004. In contrast, the first training function, with 100 epochs and a batch size of 64, reaches a maximum accuracy of 0.9883 and a loss of 0.03. Despite the first function's shorter computation time of 9 seconds, the second function's longer duration of 23 seconds is justified by its significantly higher accuracy level, which is often desired in practical applications.

5. Conclusion

In conclusion, our project focused on utilizing deep learning techniques for breast cancer detection, leveraging the Wisconsin Breast Cancer (Diagnosis) Database[6]. Through meticulous data preprocessing, model architecture design, and parameter optimization, we aimed to develop a robust algorithm capable of accurately identifying cancerous and non-cancerous cases. Our exploration involved various model architectures, activation functions, and training parameters to enhance performance.

One of the notable achievements of our project was reaching a remarkable accuracy of **1.0** for our algorithm. This accomplishment underscores the effectiveness of our approach and its potential in clinical settings for aiding in the early detection of breast cancer. Achieving such high accuracy levels is crucial in medical applications where the consequences of misdiagnosis can be severe. Moreover, the nature of the subject matter, breast cancer detection, adds another layer of significance to our project. Breast cancer is one of the most common cancers among women worldwide, making early detection a critical factor in improving treatment outcomes and survival rates. By leveraging advanced technologies like deep learning, we can augment traditional diagnostic methods and potentially reduce the burden on healthcare systems.

However, despite our successes, it's essential to acknowledge the ongoing challenges and complexities in the field of medical AI. Ethical considerations, data privacy issues, and the need for interpretability remain pertinent concerns. Furthermore, the deployment of AI algorithms in clinical practice requires rigorous validation and regulatory approval to ensure patient safety and efficacy.

In summary, our project represents a significant step forward in leveraging deep learning for breast cancer detection, showcasing the potential of AI-driven solutions in improving healthcare outcomes. Moving forward, continued research and collaboration between medical professionals, data scientists, and policymakers are essential for realizing the full potential of AI in healthcare while addressing its associated challenges.

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