TABLE I. MODELS AND THEIR ACCURACIES

S no.	Predictive Models		
	Technique	**Accuracy With PCA**	**Accuracy Without PCA**
1.	Artificial Neural Network	99.12	97.37
2.	AdaBoost	97.37	97.37
3.	AutoML(TPOT)	98.25	99.12
4.	Bagging Classifier	95.61	97.37
5.	Convolutional Neural Network	94.74	97.37
6.	Categorical Boosting	97.37	96.49
7.	Decision Trees	94.74	94.74
8.	Ensemble Methods	96.49	95.61
9.	Gaussian Mixture Model	07.02	05.26
10.	Extreme Gradient Boosting	95.61	98.25
11.	K-Means Clustering	37.71	97.71
12.	K-Nearest Neighbors	94.74	95.61
13.	Light Gradient Boosting	96.49	94.74
14.	Logistic Regression	97.37	98.25
15.	Naive Bayes	96.49	92.11
16.	Neural Networks	96.49	98.25
17.	Random Forest Model	96.49	94.74
18.	Support Vector Machines	95.61	96.49
19.	MobileNetV2	95.61	-
20.	EfficientNetB0	96.49	-
21.	DenseNet121	53.51	-
22.	Generative Adversarial Network	62.28	-

The results section of our study presents a comprehensive analysis of the performance of various machine learning and deep learning models applied to breast cancer classification. The evaluation reveals significant insights into the impact of Principal Component Analysis

(PCA) on model accuracy. Notably, Artificial Neural Networks demonstrated a remarkable accuracy improvement with PCA, suggesting its effectiveness in feature reduction. Conversely, models like AutoML (TPOT) showed higher accuracy without PCA, indicating some models benefit from the full feature set. Intriguingly, Gaussian Mixture Model and K-Means Clustering exhibited significantly lower accuracies, highlighting challenges in applying these models to this specific dataset. Advanced neural network architectures like MobileNetV2 and EfficientNetB0, although not tested with PCA, showed promising results, underscoring the potential of deep learning in medical image analysis. This diverse performance landscape underscores the need for tailored approaches in applying machine learning techniques to breast cancer diagnosis, with PCA serving as a crucial factor in optimising model accuracy.