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Machine Learning Based Decision Support System for the Diagnosis of Breast Cancer

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Abstract:- Breast cancer is among the most prevalent diseases encountered among women worldwide. Early diagnosis of breast cancer is crucial for the treatment of the disease. Detecting the disease at an early stage prevents deaths resulting from the condition. Recently, computer-aided systems have been developed to ensure early-stage diagnosis and accuracy of breast cancer. Computer-aided systems developed with machine learning approaches significantly contribute to the process of diagnosing breast cancer. The aim of this study is to propose a new classification system based on machine learning algorithms developed for the diagnosis of breast cancer. In this study, sub-data sets were created by reducing features, and data cleaning processes were applied. After these procedures, stages such as feature selection and feature extraction were applied. In this study, classification processes such as Ensemble, k-Nearest Neighbors (kNN), Support Vector Machines (SVMs), and Hybrid Artificial Intelligence were used in line with machine learning. With the obtained results, a Breast Cancer diagnosis algorithm was created. Performance evaluation criteria such as accuracy rate, specificity, sensitivity, kappa number and F-Measure were applied to the created algorithms. In the results obtained in this study, the highest accuracy rate was found to be 99.3% with the Ensemble method, the highest specificity rate was 98.7% with the Ensemble method, and the highest sensitivity rate was found to be 100% with many methods. In light of these results, it was observed that the machine learning algorithms used in this study, implemented in the Matlab environment, were effective. Consequently, it was proven that higher accuracy, specificity, and sensitivity rates can be found with different machine learning techniques. This also demonstrates that the study in our article is a reliable one in detecting diseased and healthy individuals in the diagnosis of breast cancer, showing that it is a more applicable and feasible study in the healthcare field.

Keywords:- *Breast Cancer Diagnosis; Machine Learning; Ensemble Method; Performance Review; Hybrit Artificial Intelligence.*

I. INTRODUCTION

Breast cancer is a disease where cells in the breast grow uncontrollably [1]. Breast cancer ranks among the most common cancers seen in women worldwide [2]. It is the most frequently diagnosed cancer among women in the United States [3]. Approximately 30% of newly diagnosed cancers in women each year are breast cancer [3]. It is important to understand that most breast lumps are benign and not cancerous (malignant) [4]. The histological grade of the tumor, a well-established prognostic factor, is crucial in guiding appropriate treatment in clinical practice [5]. Additionally, detecting the disease at early stages can help prevent increased mortality [6]. If left unchecked, malignant tumors can spread throughout the body and be fatal [7]. However, there is no one-size-fits-all treatment approach for breast cancer [8]. Factors such as the type and stage of breast cancer and the individual's lifestyle are considered for treatment options [8]. Generally, there are five treatment options, and most treatment plans involve a combination of the following: surgery, radiation, hormone therapy, chemotherapy, and targeted therapies [9]. Some are local and target only the area around the tumor [9]. Others are systemic and target the entire body with cancer-fighting agents [9]. Despite all these treatment methods, if cancer has spread to other parts of the body, it is usually incurable but can normally be effectively controlled for a long period [10].

In recent years, there has been an increasing trend towards the integration of computer-aided techniques in the field of breast cancer to enhance the accuracy and efficacy of diagnosis and treatment [11]. Machine learning techniques and medical imaging aid in this process [12]. Computer-aided intelligent and automated diagnostic systems developed with machine learning approaches are significant tools in analysis and can support medical professionals in the diagnosis of breast cancer, playing a role in the medical decision-making process [13]. Recently, various techniques such as deep learning, alongside machine learning techniques, have been utilized in the medical field [2], [14], [15], [16], [17]. Additionally, data mining techniques have been considered a straightforward method for understanding and predicting data [18]. Microwave imaging is also among the prevalent imaging techniques for early-stage screening and monitoring of breast cancer [19]. Despite the presentation of numerous methods, most fail to provide accurate and consistent results [2]. Moreover, existing systems require higher accuracy rates and less computation time [20]. However, all these existing studies have not yet achieved a consistent accuracy rate.

Machine learning used in the diagnosis of breast cancer is defined as the process of using data to discover hidden information that is not easily identifiable [21]. The primary goal of machine learning is to enable a system to learn without human intervention, which helps in designing an automatic system for decision-making [22]. In the literature, the use of Machine Learning (ML) has also been suggested in previous studies [23]. However, improving the prediction accuracy of the machine learning model has been seen as a significant challenge and research gap [24]. Despite all these challenges, researchers have presented numerous machine learning techniques in previous articles to address the classification difficulty of breast cancer [25].

In this study, classification processes such as Ensemble, kNN, SVMs, and Hybrid Artificial Intelligence were applied in line with machine learning. With the obtained results, a Breast Cancer diagnosis algorithm was created. Studies in the literature have shown that different machine learning and feature selection algorithms have been used on data sets with varying characteristics for breast cancer diagnosis. Various performance metrics such as accuracy, the area under the ROC curve, recall, sensitivity, specificity, and kappa statistics have been used in the literature to evaluate the performance of machine learning models. However, it has been observed that most studies do not exceed a performance criteria ratio of 99.68% in the machine learning model [26]. In this study, performance evaluation criteria similar to those in the literature, such as accuracy rate, specificity, sensitivity, kappa number, and F-Measure, were applied [27], [28]. The performance evaluation criteria specified in this study showed similarities to some studies in the literature. In studies using the same data set and similar machine learning algorithms, the highest accuracy rate was found to be 82.70% with the Random Forest method, the highest specificity rate was 84% with the SVMs method, and the highest sensitivity rate was 84% with the Extreme Boost method [29]. In the results obtained in this study, the highest accuracy rate was found to be 99.3% with the Ensemble method, the highest specificity rate was 98.7% with the Ensemble method, and the highest sensitivity rate was 100% with many methods. In some studies, as in this study, common stages such as creating sub-data sets by reducing features, data cleaning, feature selection, and feature extraction were applied, but high accuracy rates were not achieved [30], [31], [32]. In some studies, machine learning algorithms have been developed on different platforms such as R programming, Weka, Spark, and Python [33], [34], [35]. It has been observed that the machine learning algorithms applied on these platforms were less effective compared to those in this study.

II. MATERIAL AND METHODS

The workflow applied in the study is summarized in Figure 1. Initially, feature selection was performed on the breast cancer data set obtained from individuals. According to the Eta feature selection algorithm, the 14 features in the breast cancer data set were ranked starting from the best feature. Based on this ranking, 14 different sub-data sets were created. Subsequently, the sub-data sets were balanced. As a result of the data balancing process, 84 additional sub-data sets were created. Finally, classification processes such as Ensemble, kNN, SVMs, and Hybrid Artificial Intelligence were applied to the balanced sub-data sets. The diagnosis of breast cancer was attempted based on the compared classification processes.

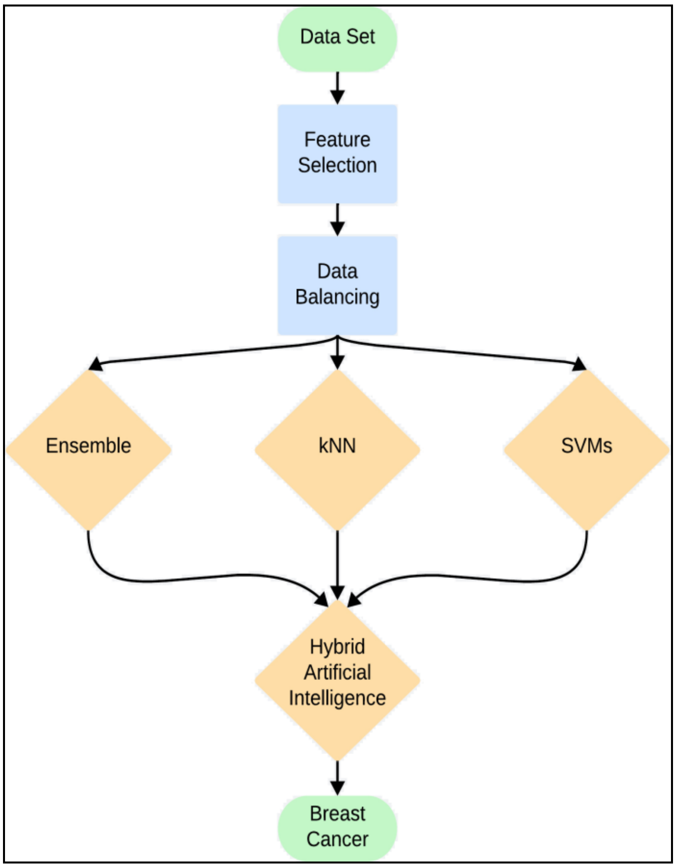

Fig 1 The Workflow in the Study

A. Data Set

The dataset utilized in this study was obtained from the publicly available website "www.kaggle.com" [36].

The dataset used in this study includes information from 4024 different individuals, encompassing age, race, marital status, T stage, N stage, stage 6, A status, tumor size, estrogen status, progesterone status, examined regional nodes, examined positive nodes, and months of survival. Based on this information, the survival and death outcomes of 4024 individuals were classified.

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Table 1 Mathematical Representation of Features and Codes [37]

No	Feature	Equation
1	Kurtosis	$x_{kur} = \frac{\sum_{i=1}^{n}(x(i)-\bar{x})^4}{(n-1)S^4}$
2	Skewness	$x_{ske} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^3}{(n-1)S^3}$
3	* IQR	$IQR = iqr(x)$
4	CV	$CV = (S/\bar{x})100$
5	Geometric Mean	$G = \sqrt[n]{x_1 + \cdots + x_n}$
6	Harmonic Mean	$H = n/(\frac{1}{x_1} + \cdots + \frac{1}{x_n})$
7	Activity - Hjort Parameters	$A = S^2$
8	Mobility - Hjort Parameters	$M = S_1^2/S^2$
9	Complexity - Hjort Parameters	$C = \sqrt{(S_2^2/S_1^2)^2 - (S_1^2/S^2)^2}$
10	* Maximum	$x_{max} = max(x_i)$
11	Median	$\tilde{x} = \begin{cases} x_{\frac{n+1}{2}} & : \ x \ odd \\ \frac{1}{2}(x_{\frac{n}{2}} + x_{\frac{n}{2}+1}) & : \ x \ even \end{cases}$
12	* Mean Absolute Deviation	$MAD = mad(x)$
13	* Minimum	$x_{min} = min(x_i)$
14	* Central Moments	$CM = moment(x, 10)$
15	Mean	$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} = \frac{1}{n}(x_1 + \cdots + x_n)$
16	Average Curve Length	$CL = \frac{1}{n}\sum_{i=2}^{n} \lvert x_i - x_{i-1} \rvert$
17	Average Energy	$E = \frac{1}{n}\sum_{i=1}^{n} x_i^2$
18	Root Mean Squared	$X_{rms} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \lvert x_i \rvert^2}$
19	Standard Error	$S_{\bar{x}} = S/\sqrt{n}$
20	Standard Deviation	$S = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})}$
21	Shape Factor	$SF = X_{rms}/(\frac{1}{n}\sum_{i=1}^{n}\sqrt{\lvert x_i \rvert})$
22	* Singular Value Decomposition	$SVD = svd(x)$
23	* 25% Trimmed Mean	$T25 = trimmean(x, 25)$
24	* 50% Trimmed Mean	$T50 = trimmean(x, 50)$
25	Average Teager Energy	$TE = \frac{1}{n}\sum_{i=3}^{n}(x_{i-1}^2 - x_i x_{i-2})$

*** The property was computed using MATLAB**
IQR Interquartile Range, CV Coefficient of Variation
S^2: variance of the signal x
S_1^2: Variance of the 1st derivative of the signal x
S_2^2: Variance of the 2nd derivative of the signal x

B. Data Preprocessing

The data has been prepared for analysis. The data preparation process, known in the literature as data preprocessing, has been elaborated in detail under the headings formulated by Han and Kamber (2006) [38]. The data preprocessing steps used in the study are outlined sequentially below.

➢ *Data Grouping*

The raw dataset comprises 14 features associated with 4024 individuals, represented with specific mathematical values. These 14 features are Age, Race, Marital Status, T Stage, N Stage, 6th Stage, Grade, A Stage, Tumor Size, Estrogen Status, Progesterone Status, Regional Node Examined, Regional Node Positive, and Survival Months. Among these, Age, Tumor Size, Regional Node Examined, Regional Node Positive, and Survival Months have numerical values and are not assigned any categorical values in the dataset. However, the other features, being non-numerical, are each assigned a numerical value. These assignments are illustrated in Table 2 and Table 3. This procedure is implemented to ensure the dataset's effective performance with artificial intelligence algorithms.

Table 2 Distribution of Features

Description of Nominal Attributes		
Attribute	**Description**	**Statement**
Race	1=White(%85), 2=Black(%7), 3= Other (American Indian/AK Native, Asian/Pacific Islander)(%8)	Race
Martial Status	1=Single (never married)(%15), 2=Divorced(%12), 3=Separated(%1), 4=Married (including common law)(%66), 5=Widowed(%6)	Martial Status
T Stage	1=T1(%40), 2=T2(%44), 3=T3(%13), 4=T4(%3)	Using the TNM system, the "T" plus a letter or number (0 to 4) is used to describe the size and location of the tumor. Tumor size is measured in centimeters (cm). A centimeter is roughly equal to the width of a standard pen or pencil.
N Stage	1=N1(%68), 2=N2(%20), 3=N3(%12)	The "N" in the TNM staging system stands for lymph nodes. These small, bean-shaped organs help fight infection. Lymph nodes near where the cancer started are called regional lymph nodes.
6th Stage	1=IIA(%32), 2=IIB(%28), 3=IIIA(%26), 4=IIIB(%2), 5=IIIC(%12)	If you have surgery as the first treatment for your cancer, your doctor will generally confirm the stage of the cancer when the testing after surgery is finalized, usually about 5 to 7 days after surgery. When systemic treatment is given before surgery, which is typically with medications and is called neoadjuvant therapy, the stage of the cancer is primarily determined clinically. Doctors may refer to stage I to stage IIA cancer as "early stage" and stage IIB to stage III as "locally advanced."
Grade	1=Well differentiated; Grade I(%13), 2=Moderately differentiated; Grade II(%58), 3=Poorly differentiated; Grade III(%28), 4=Undifferentiated; anaplastic; Grade IV(%1)	The grade describes how a cancer cell looks under the microscope and whether they are similar or very different to normal cells.
A Stage	1=Religional(%98), 2=Distant(%2)	The SEER database tracks 5-year relative survival rates for breast cancer in the United States, based on how far the cancer has spread. The SEER database, however, does not group cancers by AJCC TNM stages (stage 1, stage 2, stage 3, etc.). Instead, it groups cancers into regional and distant stages
Estrogen Status	1=Positive(%93), 2=Negative(%7)	Estrogen Status
Progesterone Status	1=Positive(%83), 2=Negative(%17)	Progesterone Status
Class	1=Alive(%85), 2=Dead(%15)	Class

Table 3 Description of Numeric Attributes

Description of Numeric Attributes							
Attribute	**Description**						**Statement**
	Min	**25%**	**50%**	**75%**	**Max**	**Mean**	
Age	39	47	54	61	69	54	Age
Tumor Size	1	16	25	38	140	30.5	Tumor Size
Regional Node Examined	1	9	14	19	61	14.4	Regional Node Examined
Regional Node Positive	1	1	2	5	46	4.16	Regional Node Positive
Survival Months	1	56	73	90	107	71.3	Survival Months

➢ *Data Balancing*

The classifications resulting from the 14 features associated with 4024 individuals in the dataset are defined under the "Class" category as either "Alive" or "Dead." However, due to the significant difference in the number of Alive and Dead individuals, the dataset underwent a data balancing process to obtain more accurate results from AI-based algorithms. Consequently, the number of Alive individuals in the dataset was sequentially divided into six segments. Each segment was combined with the Dead individuals. As a result, six different subsets of the dataset were created, each containing 568 Alive individuals and 616 Dead individuals, resulting in a total of 1184 individuals per subset. The distribution of this dataset is shown in Table 4.

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Table 4 Distribution of Training – Test Data Set

Dataset	Class		Total
	Alive	Dead	
A Dataset	568	616	**1184**
B Dataset	568	616	**1184**
C Dataset	568	616	**1184**
D Dataset	568	616	**1184**
E Dataset	568	616	**1184**
F Dataset	568	616	**1184**

C. Feature Extraction

Feature extraction was performed by calculating the dataset's features according to the specific formulas applied to data from 4024 different individuals. The formula calculations used for feature extraction are presented in **Table**. Generally, class labels are unordered categorical variables.

Table 5 Features of Data Set

Number	Attribute	Unit	Data Type
1	Age	30 – 69	Numeric
2	Race	1,2,3	Nominal
3	Martial Status	1,2,3,4,5	Nominal
4	T Stage	1,2,3,4	Nominal
5	N Stage	1,2,3	Nominal
6	6th Stage	1,2,3,4,5	Nominal
7	Grade	1,2,3,4	Nominal
8	A Stage	1,2	Nominal
9	Tumor Size	1 – 140	Numeric
10	Estrogen Status	1,2	Nominal
11	Progesterone Status	1,2	Nominal
12	Regional Node Examined	1 – 61	Numeric
13	Regional Node Positive	1 – 46	Numeric
14	Survival Months	1 – 107	Numeric
15	Class	1,2	Nominal

D. Feature Selection Algorithm

Various correlation calculation methods exist in the literature, each requiring an appropriate correlation formula based on the specific data group [39].

In this study, the Eta feature selection algorithm was employed. Eta is a method used between class labels and numerical variables. In this method, the F-Score is calculated as the threshold value. Subsequently, features are selected using two different methods: The first method selects features that exceed the threshold value. The second method ranks the features from highest to lowest and selects the top 20%. This process involves first calculating an Eta value for each feature. Then, an average Eta value is determined. According to this average, the first method selects features above the threshold value, while the second method selects the features within the top 20% based on their Eta values.

The features selected through the Eta feature selection algorithm, along with their percentage representation in the performance evaluation ranking, are shown in Table 6. The calculated correlation values of the features selected according to Eta are presented in Table 7.

Table 6 The Number of Features Selected According to the Eta Criterion

Percentage (%)	Feature Number
7	14
14	14,6
21	14,6,13
29	14,6,13,5
36	14,6,13,5,10
43	14,6,13,5,10,11
50	14,6,13,5,10,11,7
57	14,6,13,5,10,11,7,4
64	14,6,13,5,10,11,7,4,9
71	14,6,13,5,10,11,7,4,9,8
79	14,6,13,5,10,11,7,4,9,8,1

86	14,6,13,5,10,11,7,4,9,8,1,12
93	14,6,13,5,10,11,7,4,9,8,1,12,3
100	14,6,13,5,10,11,7,4,9,8,1,12,3,2

Table 7 The Correlation values of the Features Selected based on the Eta Criterion

Eta Score	**Value of the Feature**
14	0.4765
6	0.2576
13	0.2566
5	0.2558
10	0.1847
11	0.1771
7	0.1614
4	0.1547
9	0.1342
8	0.0966
1	0.0559
12	0.0348
3	0.0315
2	0.0042

E. Machine Learning Algorithms

In this study, Ensemble, k-Nearest Neighbors (kNN), Support Vector Machines (SVMs), and Hybrid Artificial Intelligence machine learning classification algorithms were employed. The classification process was conducted separately on six datasets, as indicated in Table 4, with half of the data used for model training and the other half for model testing. A training dataset was created for each data group, and the remaining data was utilized for testing. The model created from the test data was evaluated using performance evaluation criteria to assess its effectiveness.

➢ *Ensemble Decision Trees*

Ensemble decision trees are algorithm-based systems that are essential for data interpretation, particularly for large datasets. These trees generate algorithms that provide systematic guidance. Unlike standard decision trees, ensemble decision trees compare all decision trees within the system and integrate them into a single, unified decision tree.

For instance: In the context of deciding whether to rent or buy a house, variables such as price, number of rooms, and square footage are considered. The output variable is binary, indicating either yes (rent or buy) or no. When determining criteria such as a price below X and square footage of at least Y, a decision tree model is effectively constructed [40]. Fig 2 illustrates the decision tree model.

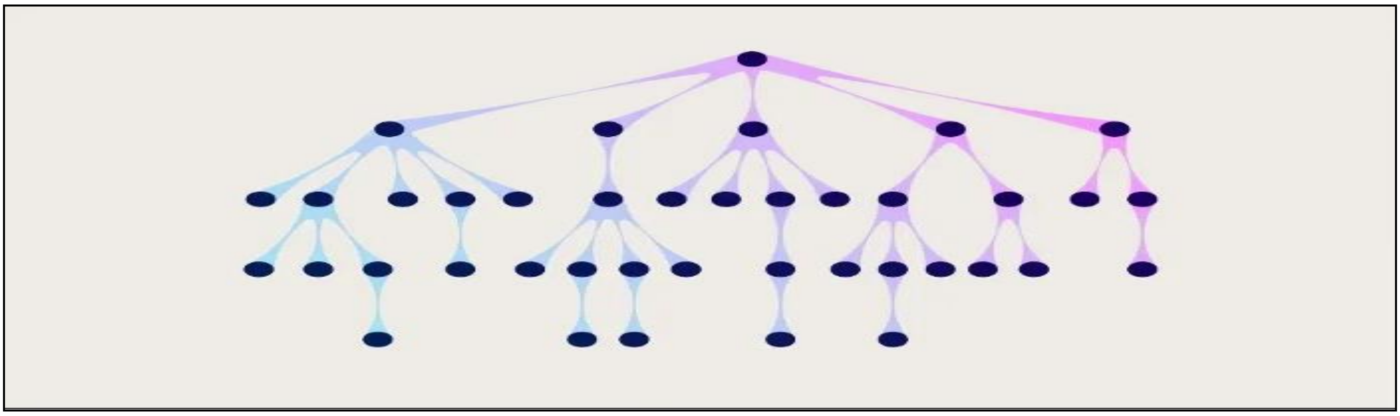

Fig 2 Ensemble Decision Trees [41]

➢ *k Nearest Neighbor (kNN)*

In the k-Nearest Neighbor Algorithm, the classification of a data point is determined by examining the closest data points around it, based on the distribution of the data. The term "k" refers to the number of nearest data points to be considered when determining the value of the target data point. Generally, "k" is chosen as an odd number to ensure a more robust decision-making process in the system [42]. As illustrated in Fig 3, the data point whose value is to be determined is classified into the category that encompasses the majority of its neighbors within a specified radius. Since "k" is typically an odd number, the possibility of a tie is avoided. Euclidean and Manhattan distance functions are commonly used to calculate the distances between data points.

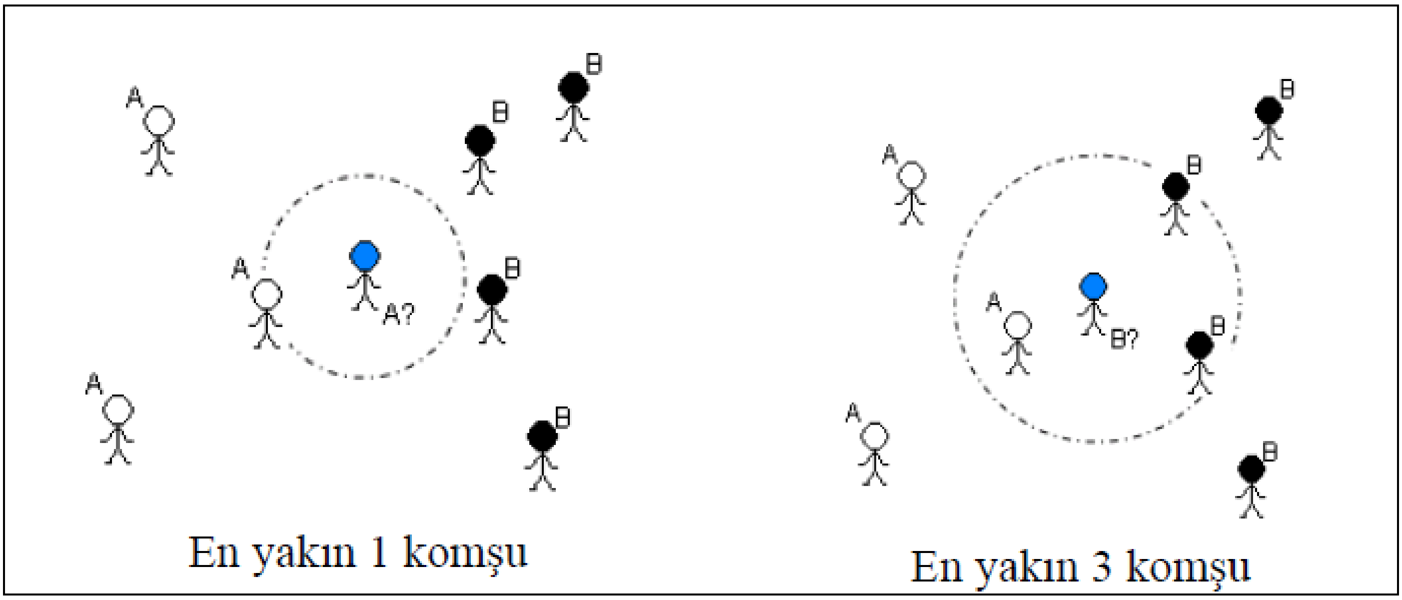

Fig 3 k-Nearest Neighbors (kNN) [43]

➢ *Support Vector Machines (SVMs)*

Similar to kNN, in Support Vector Machines (SVMs), all data points are plotted on an x-y axis based on their features. A curve is then fitted to separate the two features. This curve is generated by optimizing the features within the dataset and can be either linear or non-linear. The data points that fall above and below the curve are then classified accordingly. For example, if the curve is a circle, the data points can be grouped as those inside or outside the circle [44].

Fig 4 shows an example of Support Vector Machines with both linear and non-linear features created using two features on a two-axis system.

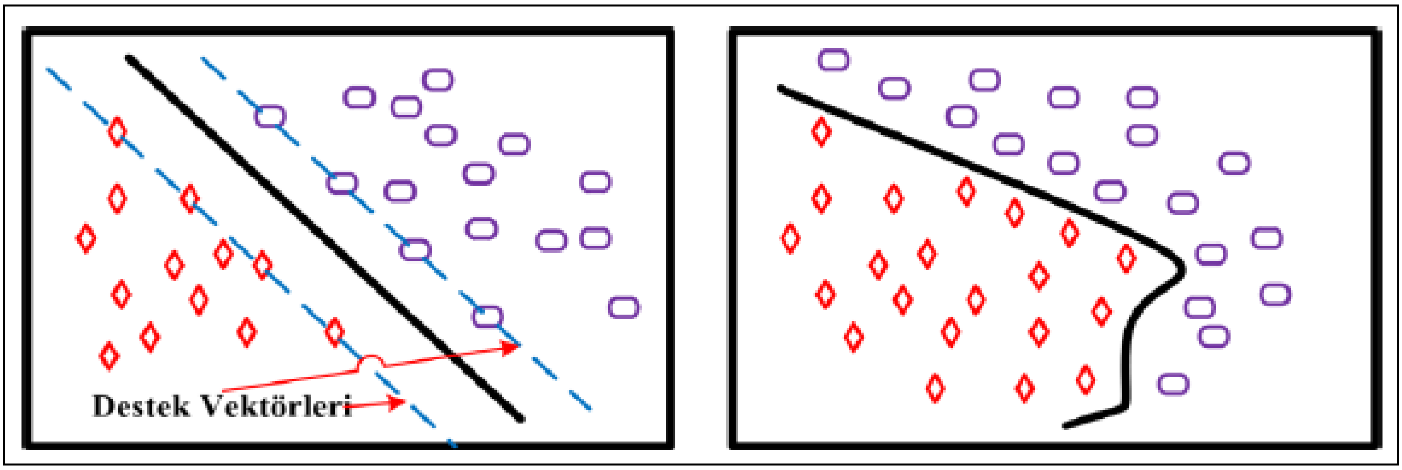

Fig 4 Support Vector Machines (SVMs) [45]

➢ *Hybrid Artificial Intelligence*

This method is based on the arithmetic average of the classification decisions generated by applying kNN, Decision Trees, and Support Vector Machines (SVMs) algorithms to the data. Essentially, the outcome of Hybrid Artificial Intelligence corresponds to the majority decision among these methods. The weaknesses of the individual classification algorithms do not affect the final decision in Hybrid Artificial Intelligence. The goal is to combine weak classifiers to form a strong classifier under the name of Hybrid Artificial Intelligence. The performance improves as the number of classification algorithms used in the Hybrid AI increases.

The hybrid method is quite similar to the Ensemble Decision Trees method. Another name for the hybrid method could be "Ensemble." Both methods aim to combine multiple artificial intelligence algorithms—typically 99 in number. In the Ensemble method, only decision trees are combined, whereas the goal of the hybrid method is to integrate different algorithms. The number of algorithms used in the hybrid method is typically odd (e.g., 1, 3, 5, 7, ... n). The primary distinction between Hybrid AI and Ensemble Decision Trees is that the former does not involve decision trees. Instead, Hybrid AI makes its decision by averaging the outcomes of different algorithms, without deriving a decision tree.

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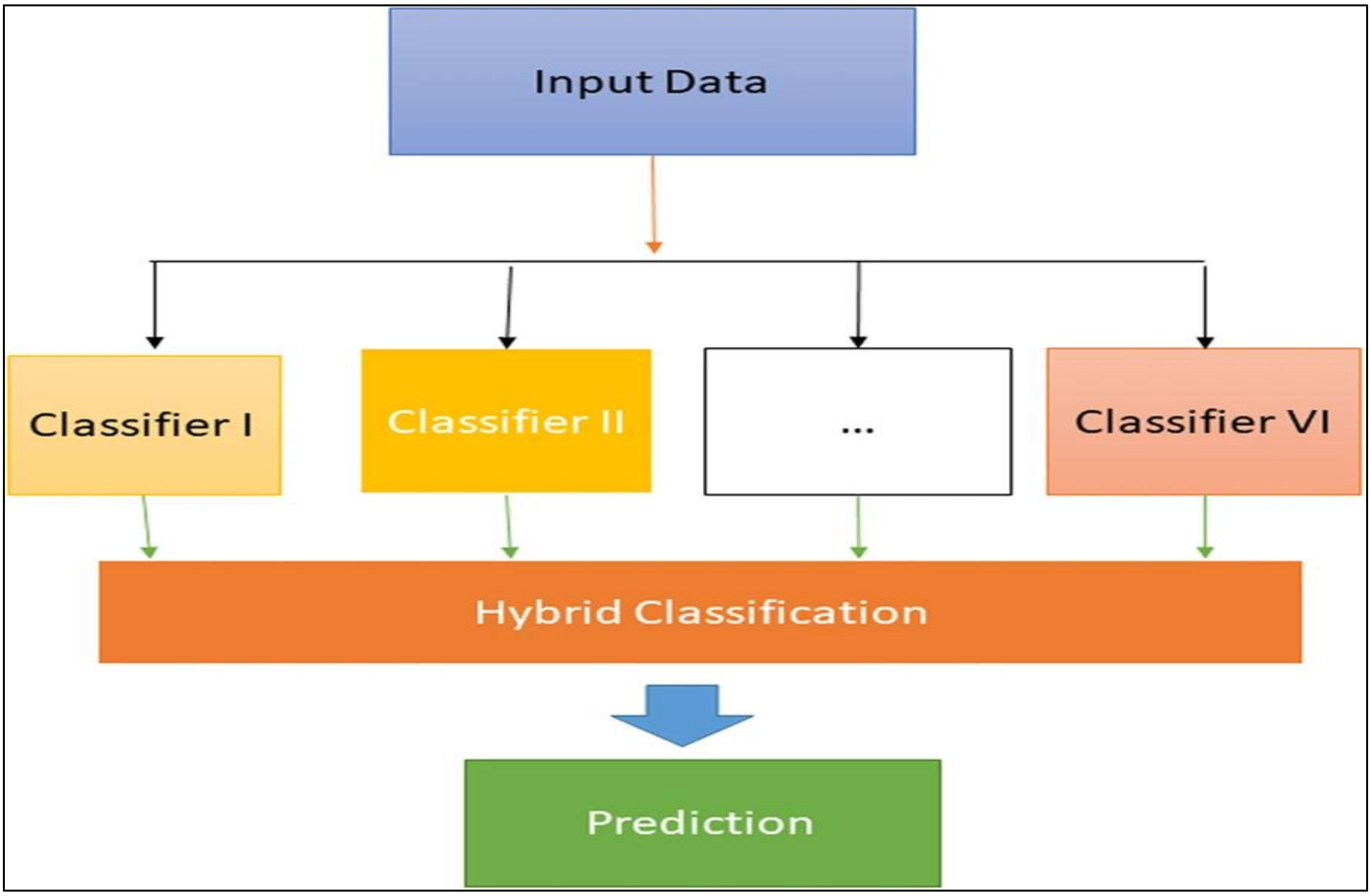

Fig 5 Hybrid Artificial Intelligence [46]

Consider an example where n data points, such as data points 1, 2, and 3, are input into the system. In the Hybrid method, it is crucial that the number of data points, n, is odd, as an even number of data points can lead to an indeterminate result, making the Hybrid method ineffective.

For instance, for data point 1, the kNN method might classify the individual as sick, assigning label 1; the Conditional Decision Tree (Ctree) method might classify the individual as healthy, assigning label 2; and the SVM method might classify the individual as sick, assigning label 1. The Hybrid method calculates the average of these three methods, resulting in a value of 1.33333, as shown in Table 8. This value is then rounded, and the final classification for data point 1, based on the majority rule, is determined as healthy.

In the Hybrid method, whether the average of the method labels or the majority rule is applied, the outcome is consistent.

The underlying principle of the Hybrid method is to adopt the decision that reflects the majority.

Table 8 Example Table of Hybrid Artificial Intelligence

Veri	**kNN**	**Ctree**	**SVMs**	**Hibrit**	**Gerçek**
1	1	2	1	1.333333	1
2	2	2	1	1.666667	2
3	2	1	1	1.333333	1

As shown in Table 8, each method used in the study demonstrates weaknesses when analyzing the labels produced. For instance, Ctree shows a weakness with label 1, SVMs with label 2, and kNN with label 1.

The primary objective of the Hybrid method is to combine weak classifiers (Ctree, SVMs, and kNN) to form a stronger classifier. When each method is applied individually to data points 1, 2, and 3, each method correctly classifies two out of the three data points. However, when the Hybrid method is applied, it correctly classifies all three data points according to the actual values. Thus, the Hybrid method aims to aggregate weak classifiers into a robust classifier.

- *This Concept can be Explained with the Following Example:*

Consider a table with four legs. If one person, lacking sufficient strength, attempts to lift the table, they are unable to do so. However, if four individuals, each with similar strength, lift the table together, they succeed. While the table may be unstable when lifted by one person, the likelihood of it falling decreases when four people lift it together. The principle of the Hybrid method is analogous: as the number of classifiers increases, the performance of the Hybrid method correspondingly improves.

F. Performance Evaluation Criteria

The study utilized performance evaluation criteria such as accuracy, specificity, sensitivity, kappa statistic, and F-measure [27], [28]. These criteria were applied to the Ensemble, kNN, SVMs, and Hybrid Artificial Intelligence classifiers.

The training-test split ratio for dataset classification was set at 50%-50%, as shown in Table 9.

Table 9 Training-Test Dataset Distribution (Sample Distribution Table)

Class	A Dataset		
	Training(%50)	**Test(%50)**	**Total**
Alive (Group 1)	284	284	**568**
Dead	308	308	**616**
Total	**592**	**592**	**1184**
Class	**B Dataset**		
	Training(%50)	**Test(%50)**	**Total**
Alive (Group 2)	284	284	**568**
Dead	308	308	**616**
Total	**592**	**592**	**1184**
Class	**C Dataset**		
	Training(%50)	**Test(%50)**	**Total**
Alive (Group 3)	284	284	**568**
Dead	308	308	**616**
Total	**592**	**592**	**1184**
Class	**D Dataset**		
	Training(%50)	**Test(%50)**	**Total**
Alive (Group 4)	284	284	**568**
Dead	308	308	**616**
Total	**592**	**592**	**1184**
Class	**E Dataset**		
	Training(%50)	**Test(%50)**	**Total**
Alive (Group 5)	284	284	**568**
Dead	308	308	**616**
Total	**592**	**592**	**1184**
Class	**F Dataset**		
	Training(%50)	**Test(%50)**	**Total**
Alive (Group 6)	284	284	**568**
Dead	308	308	**616**
Total	**592**	**592**	**1184**

III. RESULTS

The objective of this study is to develop a rule-based diagnostic algorithm for breast cancer using artificial intelligence methods. The dataset used in the study includes diagnostic outcomes for individuals based on 14 clinical findings. The Eta feature selection algorithm was applied to the dataset, ranking the 14 features from the most significant to the least. Based on this ranking, 14 different subsets of the dataset were created. Due to the imbalance in the dataset concerning the class variable, these subsets underwent data balancing procedures, resulting in 84 additional subsets. These 84 subsets were generated by evaluating six different datasets derived from the original class dataset, with each dataset being analyzed separately based on the 14 ranked features. All balanced datasets were classified using Ensemble, kNN, SVMs, and Hybrid Artificial Intelligence methods. Based on the results, a diagnostic algorithm for breast cancer was developed.

According to Table 10 and Table 11, the performance evaluation criteria (accuracy, sensitivity, specificity, F1-score, kappa, and AUC) for the A Dataset in Table 9—across all classification models (SVMs, kNN, Ensemble, and Hybrid)—initially decreased when ranked from the best to the top 7 features, and then increased as the number of features expanded to 14. Overall, when examining the ranking of the 14 features, the Ensemble method was identified as the most successful classification approach. The highest performance evaluation metrics within the Ensemble classification method were observed in the dataset containing the top 13 features. In Fig 6, it is visually evident that the Ensemble classification method occupies the largest area when compared to other methods, especially when considering the dataset with the top 13 features.

According to Table 12 and Table 13, the performance evaluation criteria (accuracy, sensitivity, specificity, F1-score, kappa, and AUC) for the B Dataset in Table 9—across

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all classification models (SVMs, kNN, Ensemble, and Hybrid)—initially decreased when ranked from the best to the top 13 features, and then increased at the 14th feature. Overall, when examining the ranking of the 14 features, the Ensemble method was identified as the most successful classification approach. However, alongside the Ensemble method, the kNN and Hybrid classification methods also demonstrated equally high performance metrics within the dataset containing the top 1 feature. In Fig 7, it is visually evident that the Ensemble, kNN, and Hybrid classification methods occupy the largest area when considering the dataset with the top 1 feature, compared to other methods.

According to Table 14 and Table 15, the performance evaluation criteria (accuracy, sensitivity, specificity, F1-score, kappa, and AUC) for the C Dataset in Table 9—across all classification models (SVMs, kNN, Ensemble, and Hybrid)—initially decreased when ranked from the best to the top 7 features, and then increased as the number of features expanded to 14. Overall, when examining the ranking of the 14 features, the Ensemble method was identified as the most successful classification approach. However, alongside the Ensemble method, the kNN and Hybrid classification methods also demonstrated equally high performance metrics within the dataset containing the top 1 feature. In Fig 8, it is visually evident that the Ensemble, kNN, and Hybrid classification methods occupy the largest area when considering the dataset with the top 1 feature, compared to other methods.

According to Table 16 and Table 17, the performance evaluation criteria (accuracy, sensitivity, specificity, F1-score, kappa, and AUC) for the D Dataset in Table 9—across all classification models (SVMs, kNN, Ensemble, and Hybrid)—initially decreased when ranked from the best to the top 7 features, and then increased as the number of features expanded to 14. Overall, when examining the ranking of the 14 features, the Hybrid method was identified as the most successful classification approach. However, alongside the Hybrid method, the kNN and Ensemble classification methods also demonstrated equally high performance metrics within the dataset containing the top 1 feature. In Fig 9, it is visually evident that the Ensemble, kNN, and Hybrid classification methods occupy the largest area when considering the dataset with the top 1 feature, compared to other methods.

According to Table 18 and Table 19, the performance evaluation criteria (accuracy, sensitivity, specificity, F1-score, kappa, and AUC) for the E Dataset in Table 9—across all classification models (SVMs, kNN, Ensemble, and Hybrid)—initially decreased when ranked from the best to the top 7 features, and then increased as the number of features expanded to 14. Overall, when examining the ranking of the 14 features, the SVMs method was identified as the most successful classification approach. However, within the Ensemble classification method, the highest performance metrics were observed in the dataset containing the top 1 feature. In Fig 10, it is visually evident that the Ensemble classification method occupies the largest area when considering the dataset with the top 1 feature, compared to other methods.

According to Table 20 and Table 21, the performance evaluation criteria (accuracy, sensitivity, specificity, F1-score, kappa, and AUC) for the F Dataset in Table 9—across all classification models (SVMs, kNN, Ensemble, and Hybrid)—initially decreased when ranked from the best to the top 7 features, and then increased as the number of features expanded to 14. Overall, when examining the ranking of the 14 features, the Ensemble method was identified as the most successful classification approach. Within the Ensemble classification method, the highest performance metrics were observed in the dataset containing the top 2 features. In Fig 11, it is visually evident that the Ensemble classification method occupies the largest area when considering the dataset with the top 2 features, compared to other methods.

According to Table 9, when analyzing the methods applied across all datasets, it is observed that the sensitivity value is higher than the accuracy value, indicating a higher rate of disease detection. This suggests that the system is effective in identifying individuals with breast cancer. The system is particularly effective in the early detection of breast cancer in affected individuals.As shown in Table 18, Table 19, and Fig 10, the Ensemble method applied to the E Dataset, which utilizes the top 1 feature, along with the SVMs classification method applied to the datasets with the top 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, and 13 features, all achieve a sensitivity rate of 100%, indicating the highest and most consistent sensitivity performance. However, when considering the overall system performance across all datasets, the specificity value is observed to be lower than the sensitivity value. This implies that the system is less effective in identifying healthy individuals compared to its ability to detect cancerous cases. Consequently, the likelihood of a breast cancer patient being misclassified as healthy is low, and the system prioritizes the accurate detection of cancerous patients.

In the overall application, the accuracy rate of the system is generally above 90% across all datasets, as shown in Table 9 Training-Test Dataset Distribution (Sample Distribution Table). This high accuracy rate suggests that the system is highly suitable for use in the healthcare field. Specifically, the F Dataset, as shown in Table 20, Table 21, and Fig 11, predominantly achieves the highest accuracy rates within the Ensemble classification method. The dataset using the Ensemble classification method with the top 2 features in the F Dataset achieves the highest accuracy rate of 99.3%. In the study, feature extraction was performed using the best single feature, as demonstrated in Table 12, Table 13, and Fig 7; Table 14, Table 15, and Fig 8; Table 16, Table 17, and Fig 9; and Table 18, Table 19, and Fig 10. Additionally, feature extraction using the best two features was shown in Table 20, Table 21, and Fig 11. These results demonstrate and visualize that the system can achieve efficient outcomes with reduced computational workload by extracting fewer features.

Table 10 A Dataset Summary Table – Best Methods

L	FN	FP	Model	Accuracy	Sensitivity	Specificity	F1 Score	Kappa	AUC
1	1	7.14	SVMs	100.0	100.0	NaN	NaN	0.0	50.0
			kNN	72.5	97.5	49.4	65.5	45.9	73.4
			Ensemble	***82.1***	***79.6***	***84.4***	***81.9***	***64.1***	***82.0***
			Hybrid	***82.1***	***79.6***	***84.4***	***81.9***	***64.1***	***82.0***
2	2	14.28	SVMs	63.7	67.3	60.4	63.6	27.5	63.8
			kNN	76.2	91.9	61.7	73.8	52.9	76.8
			Ensemble	***80.4***	***82.0***	***78.9***	***80.4***	***60.8***	***80.5***
			Hybrid	79.4	87.7	71.8	78.9	59.0	79.7
3	3	21.42	SVMs	59.3	87.7	33.1	48.1	20.3	60.4
			kNN	78.4	85.6	71.8	78.1	57.0	78.7
			Ensemble	***79.2***	***78.9***	***79.5***	***79.2***	***58.4***	***79.2***
			Hybrid	78.4	84.2	73.1	78.2	56.9	78.6
4	4	28.56	SVMs	63.3	74.3	53.2	62.0	27.3	63.8
			kNN	78.0	84.9	71.8	77.8	56.3	78.3
			Ensemble	***78.4***	***79.9***	***76.9***	***78.4***	***56.8***	***78.4***
			Hybrid	78.2	82.7	74.0	78.1	56.5	78.4
5	5	35.7	SVMs	61.1	86.3	38.0	52.7	23.8	62.1
			kNN	77.9	85.2	71.1	77.5	56.0	78.2
			Ensemble	***79.4***	***81.0***	***77.9***	***79.4***	***58.8***	***79.5***
			Hybrid	78.7	84.5	73.4	78.5	57.6	78.9
6	6	42.84	SVMs	64.9	81.0	50.0	61.8	30.6	65.5
			kNN	78.2	86.6	70.5	77.7	56.7	78.5
			Ensemble	79.2	79.6	78.9	79.2	58.4	79.2
			Hybrid	***79.2***	***83.8***	***75.0***	***79.2***	***58.6***	***79.4***
7	7	49.98	SVMs	66.9	81.0	53.9	64.7	34.5	67.4
			kNN	77.7	85.6	70.5	77.3	55.6	78.0
			Ensemble	77.5	76.8	78.2	77.5	55.0	77.5
			Hybrid	***78.5***	***81.7***	***75.6***	***78.6***	***57.2***	***78.7***

Table 11 A Dataset Summary Table – Best Methods(continue)

L	FN	FP	Model	Accuracy	Sensitivity	Specificity	F1 Score	Kappa	AUC
8	8	57.12	SVMs	66.7	78.2	56.2	65.4	34.0	67.2
			kNN	77.0	83.1	71.4	76.8	54.2	77.3
			Ensemble	78.5	78.5	78.6	78.5	57.1	78.5
			Hybrid	**78.9**	**81.0**	**76.9**	**78.9**	**57.8**	**79.0**
9	9	64.26	SVMs	66.4	79.2	54.5	64.6	33.4	66.9
			kNN	76.9	81.0	73.1	76.8	53.8	77.0
			Ensemble	***81.1***	***82.7***	***79.5***	***81.1***	***62.2***	***81.1***
			Hybrid	80.6	84.2	77.3	80.6	61.2	80.7
10	10	71.4	SVMs	66.2	78.9	54.5	64.5	33.1	66.7
			kNN	76.9	81.0	73.1	76.8	53.8	77.0
			Ensemble	***81.1***	***82.4***	***79.9***	***81.1***	***62.2***	***81.1***
			Hybrid	80.9	83.8	78.2	80.9	61.9	81.0
11	11	78.54	SVMs	66.2	77.8	55.5	64.8	33.0	66.7
			kNN	74.8	77.8	72.1	74.8	49.7	74.9
			Ensemble	***81.4***	***82.4***	***80.5***	***81.4***	***62.8***	***81.5***
			Hybrid	79.7	83.1	76.6	79.7	59.5	79.9
12	12	85.68	SVMs	67.4	78.2	57.5	66.2	35.3	67.8
			kNN	71.6	74.6	68.8	71.6	43.3	71.7
			Ensemble	***82.3***	***85.2***	***79.5***	***82.3***	***64.6***	***82.4***
			Hybrid	79.1	83.8	74.7	79.0	58.2	79.2
13	13	92.82	SVMs	68.6	79.2	58.8	67.5	37.6	69.0
			kNN	72.3	76.1	68.8	72.3	44.7	72.4
			Ensemble	***83.1***	***86.3***	***80.2***	***83.1***	***66.3***	***83.2***
			Hybrid	80.7	85.2	76.6	80.7	61.6	80.9
14	14	99.96	SVMs	68.2	77.8	59.4	67.4	36.9	68.6
			kNN	71.8	75.4	68.5	71.8	43.7	71.9
			Ensemble	***83.1***	***85.2***	***81.2***	***83.1***	***66.2***	***83.2***
			Hybrid	80.1	82.7	77.6	80.1	60.2	80.2

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Table 12 B Dataset Summary Table – Best Methods

L	FN	FP	Model	Accuracy	Sensitivity	Specificity	F1 Score	Kappa	AUC
1	1	7.14	SVMs	78.2	100.0	58.1	73.5	57.1	79.1
			kNN	***93.4***	***100.0***	***87.3***	***93.2***	***86.9***	***93.7***
			Ensemble	***93.4***	***100.0***	***87.3***	***93.2***	***86.9***	***93.7***
			Hybrid	***93.4***	***100.0***	***87.3***	***93.2***	***86.9***	***93.7***
2	2	14.28	SVMs	78.0	93.7	63.6	75.8	56.6	78.6
			kNN	93.6	100.0	87.7	93.4	87.2	93.8
			Ensemble	93.4	97.2	89.9	93.4	86.8	93.6
			Hybrid	**93.9**	**99.3**	**89.0**	**93.8**	**87.9**	**94.1**
3	3	21.42	SVMs	77.4	92.6	63.3	75.2	55.2	78.0
			kNN	***92.4***	***95.4***	***89.6***	***92.4***	***84.8***	***92.5***
			Ensemble	91.6	92.3	90.9	91.6	83.1	91.6
			Hybrid	92.2	94.7	89.9	92.3	84.5	92.3
4	4	28.56	SVMs	76.5	93.0	61.4	73.9	53.6	77.2
			kNN	92.4	95.4	89.6	92.4	84.8	92.5
			Ensemble	91.7	93.3	90.3	91.8	83.4	91.8
			Hybrid	***92.6***	***95.8***	***89.6***	***92.6***	***85.2***	***92.7***
5	5	35.7	SVMs	76.4	93.0	61.0	73.7	53.3	77.0
			kNN	***92.1***	***95.4***	***89.0***	***92.1***	***84.1***	***92.2***
			Ensemble	90.7	91.5	89.9	90.7	81.4	90.7
			Hybrid	91.6	94.4	89.0	91.6	83.1	91.7
6	6	42.84	SVMs	76.4	92.3	61.7	73.9	53.2	77.0
			kNN	***91.4***	***94.4***	***88.6***	***91.4***	***82.8***	***91.5***
			Ensemble	90.9	91.9	89.9	90.9	81.7	90.9
			Hybrid	91.0	93.7	88.6	91.1	82.1	91.1
7	7	49.98	SVMs	76.2	89.8	63.6	74.5	52.8	76.7
			kNN	***91.0***	***93.3***	***89.0***	***91.1***	***82.1***	***91.1***
			Ensemble	88.9	88.0	89.6	88.8	77.7	88.8
			Hybrid	90.2	91.9	88.6	90.2	80.4	90.3

Table 13 B Dataset Summary Table – Best Methods (Continue)

L	FN	FP	Model	Accuracy	Sensitivity	Specificity	F1 Score	Kappa	AUC
8	8	57.12	SVMs	76.2	89.8	63.6	74.5	52.8	76.7
			kNN	**91.2**	**93.7**	**89.0**	**91.3**	**82.4**	**91.3**
			Ensemble	89.4	89.4	89.3	89.4	78.7	89.4
			Hybrid	90.4	92.3	88.6	90.4	80.7	90.4
9	9	64.26	SVMs	76.0	90.5	62.7	74.0	52.5	76.6
			kNN	87.8	90.5	85.4	87.9	75.7	87.9
			Ensemble	**91.9**	**94.4**	**89.6**	**91.9**	**83.8**	**92.0**
			Hybrid	91.2	96.1	86.7	91.2	82.5	91.4
10	10	71.4	SVMs	76.0	90.5	62.7	74.0	52.5	76.6
			kNN	87.8	90.5	85.4	87.9	75.7	87.9
			Ensemble	**91.4**	**93.7**	**89.3**	**91.4**	**82.8**	**91.5**
			Hybrid	90.7	95.8	86.0	90.6	81.5	90.9
11	11	78.54	SVMs	76.4	88.7	64.9	75.0	53.1	76.8
			kNN	86.7	89.8	83.8	86.7	73.3	86.8
			Ensemble	**91.2**	**93.7**	**89.0**	**91.3**	**82.4**	**91.3**
			Hybrid	88.9	93.0	85.1	88.8	77.7	89.0
12	12	85.68	SVMs	75.8	89.1	63.6	74.2	52.1	76.4
			kNN	83.8	87.0	80.8	83.8	67.6	83.9
			Ensemble	**91.7**	**94.4**	**89.3**	**91.8**	**83.5**	**91.8**
			Hybrid	88.7	94.4	83.4	88.6	77.4	88.9
13	13	92.82	SVMs	76.2	89.1	64.3	74.7	52.8	76.7
			kNN	83.8	86.6	81.2	83.8	67.6	83.9
			Ensemble	**91.4**	**94.4**	**88.6**	**91.4**	**82.8**	**91.5**
			Hybrid	88.2	92.6	84.1	88.1	76.4	88.3
14	14	99.96	SVMs	75.3	88.7	63.0	73.7	51.1	75.9
			kNN	83.4	85.9	81.2	83.5	66.9	83.5
			Ensemble	**92.1**	**94.7**	**89.6**	**92.1**	**84.1**	**92.2**
			Hybrid	88.2	93.0	83.8	88.1	76.4	88.4

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Table 14 C Dataset Summary Table – Best Methods

L	FN	FP	Model	Accuracy	Sensitivity	Specificity	F1 Score	Kappa	AUC
1	1	7.14	SVMs	86.7	100.0	74.4	85.3	73.6	87.2
			kNN	***96.1***	***100.0***	***92.5***	***96.1***	***92.2***	***96.3***
			Ensemble	***96.1***	***100.0***	***92.5***	***96.1***	***92.2***	***96.3***
			Hybrid	***96.1***	***100.0***	***92.5***	***96.1***	***92.2***	***96.3***
2	2	14.28	SVMs	86.5	100.0	74.0	85.1	73.2	87.0
			kNN	95.6	99.6	91.9	95.6	91.2	95.8
			Ensemble	***95.9***	***99.3***	***92.9***	***96.0***	***91.9***	***96.1***
			Hybrid	95.6	99.6	91.9	95.6	91.2	95.8
3	3	21.42	SVMs	85.6	98.6	73.7	84.3	71.5	86.1
			kNN	***94.8***	***97.5***	***92.2***	***94.8***	***89.5***	***94.9***
			Ensemble	94.8	96.1	93.5	94.8	89.5	94.8
			Hybrid	94.6	97.2	92.2	94.6	89.2	94.7
4	4	28.56	SVMs	85.3	97.9	73.7	84.1	70.9	85.8
			kNN	***94.8***	***97.5***	***92.2***	***94.8***	***89.5***	***94.9***
			Ensemble	94.8	96.1	93.5	94.8	89.5	94.8
			Hybrid	94.6	97.2	92.2	94.6	89.2	94.7
5	5	35.7	SVMs	85.3	97.9	73.7	84.1	70.9	85.8
			kNN	94.4	96.8	92.2	94.5	88.9	94.5
			Ensemble	***94.8***	***96.5***	***93.2***	***94.8***	***89.5***	***94.8***
			Hybrid	94.6	97.2	92.2	94.6	89.2	94.7
6	6	42.84	SVMs	85.5	97.9	74.0	84.3	71.2	86.0
			kNN	***94.4***	***96.5***	***92.5***	***94.5***	***88.9***	***94.5***
			Ensemble	93.9	94.0	93.8	93.9	87.8	93.9
			Hybrid	***94.4***	***96.5***	***92.5***	***94.5***	***88.9***	***94.5***
7	7	49.98	SVMs	86.8	97.9	76.6	86.0	73.8	87.3
			kNN	93.4	95.1	91.9	93.4	86.8	93.5
			Ensemble	92.4	91.5	93.2	92.4	84.8	92.4
			Hybrid	***93.8***	***95.8***	***91.9***	***93.8***	***87.5***	***93.8***

Table 15 C Dataset Summary Table – Best Methods(continue)

L	FN	FP	Model	Accuracy	Sensitivity	Specificity	F1 Score	Kappa	AUC
8	8	57.12	SVMs	86.7	97.5	76.6	85.8	73.5	87.1
			kNN	93.6	94.7	92.5	93.6	87.2	93.6
			Ensemble	93.6	94.0	93.2	93.6	87.1	93.6
			Hybrid	***93.9***	***96.1***	***91.9***	***94.0***	***87.8***	***94.0***
9	9	64.26	SVMs	85.8	96.5	76.0	85.0	71.8	86.2
			kNN	91.9	94.4	89.6	91.9	83.8	92.0
			Ensemble	***95.3***	***97.2***	***93.5***	***95.3***	***90.5***	***95.3***
			Hybrid	94.1	97.5	90.9	94.1	88.2	94.2
10	10	71.4	SVMs	86.0	96.8	76.0	85.1	72.2	86.4
			kNN	91.9	94.4	89.6	91.9	83.8	92.0
			Ensemble	***95.1***	***97.2***	***93.2***	***95.1***	***90.2***	***95.2***
			Hybrid	93.8	97.2	90.6	93.8	87.5	93.9
11	11	78.54	SVMs	86.5	96.1	77.6	85.9	73.1	86.9
			kNN	89.5	93.0	86.4	89.5	79.1	89.7
			Ensemble	***95.4***	***96.8***	***94.2***	***95.5***	***90.9***	***95.5***
			Hybrid	92.9	98.2	88.0	92.8	85.8	93.1
12	12	85.68	SVMs	86.3	96.8	76.6	85.6	72.8	86.7
			kNN	89.7	94.0	85.7	89.7	79.4	89.9
			Ensemble	***95.9***	***98.2***	***93.8***	***96.0***	***91.9***	***96.0***
			Hybrid	92.9	98.9	87.3	92.8	85.9	93.1
13	13	92.82	SVMs	86.1	96.8	76.3	85.3	72.5	86.6
			kNN	89.5	94.0	85.4	89.5	79.1	89.7
			Ensemble	***95.9***	***98.2***	***93.8***	***96.0***	***91.9***	***96.0***
			Hybrid	92.9	98.9	87.3	92.8	85.9	93.1
14	14	99.96	SVMs	86.0	96.5	76.3	85.2	72.2	86.4
			kNN	89.5	94.0	85.4	89.5	79.1	89.7
			Ensemble	***95.8***	***98.2***	***93.5***	***95.8***	***91.6***	***95.9***
			Hybrid	92.7	98.9	87.0	92.6	85.5	93.0

Table 16 D Dataset Summary Table – Best Methods

L	FN	FP	Model	Accuracy	Sensitivity	Specificity	F1 Score	Kappa	AUC
1	1	7.14	SVMs	91.2	100.0	83.1	90.8	82.5	91.6
			kNN	***95.9***	***100.0***	***92.2***	***95.9***	***91.9***	***96.1***
			Ensemble	***95.9***	***100.0***	***92.2***	***95.9***	***91.9***	***96.1***
			Hybrid	***95.9***	***100.0***	***92.2***	***95.9***	***91.9***	***96.1***
2	2	14.28	SVMs	91.4	100.0	83.4	91.0	82.9	91.7
			kNN	95.3	100.0	90.9	95.2	90.6	95.5
			Ensemble	***95.9***	***100.0***	***92.2***	***95.9***	***91.9***	***96.1***
			Hybrid	95.3	100.0	90.9	95.2	90.6	95.5
3	3	21.42	SVMs	91.4	100.0	83.4	91.0	82.9	91.7
			kNN	93.4	95.1	91.9	93.4	86.8	93.5
			Ensemble	93.1	93.0	93.2	93.1	86.1	93.1
			Hybrid	***93.4***	***95.4***	***91.6***	***93.5***	***86.8***	***93.5***
4	4	28.56	SVMs	91.4	100.0	83.4	91.0	82.9	91.7
			kNN	93.6	95.1	92.2	93.6	87.2	93.6
			Ensemble	93.6	94.0	93.2	93.6	87.1	93.6
			Hybrid	***93.6***	***95.4***	***91.9***	***93.6***	***87.2***	***93.7***
5	5	35.7	SVMs	91.4	100.0	83.4	91.0	82.9	91.7
			kNN	***93.2***	***94.7***	***91.9***	***93.3***	***86.5***	***93.3***
			Ensemble	93.1	93.3	92.9	93.1	86.1	93.1
			Hybrid	***93.2***	***95.1***	***91.6***	***93.3***	***86.5***	***93.3***
6	6	42.84	SVMs	91.4	100.0	83.4	91.0	82.9	91.7
			kNN	***93.1***	***94.4***	***91.9***	***93.1***	***86.1***	***93.1***
			Ensemble	92.4	91.9	92.9	92.4	84.8	92.4
			Hybrid	***93.1***	***94.7***	***91.6***	***93.1***	***86.1***	***93.1***
7	7	49.98	SVMs	91.4	100.0	83.4	91.0	82.9	91.7
			kNN	93.1	94.4	91.9	93.1	86.1	93.1
			Ensemble	92.4	91.5	93.2	92.4	84.8	92.4
			Hybrid	***93.2***	***94.7***	***91.9***	***93.3***	***86.5***	***93.3***

Table 17 D Dataset Summary Table – Best Methods (Continue)

L	FN	FP	Model	Accuracy	Sensitivity	Specificity	F1 Score	Kappa	AUC
8	8	57.12	SVMs	91.6	100.0	83.8	91.2	83.2	91.9
			kNN	93.2	94.4	92.2	93.3	86.5	93.3
			Ensemble	93.2	93.3	93.2	93.2	86.5	93.2
			Hybrid	***93.8***	***95.4***	***92.2***	***93.8***	***87.5***	***93.8***
9	9	64.26	SVMs	91.4	100.0	83.4	91.0	82.9	91.7
			kNN	93.1	96.8	89.6	93.1	86.2	93.2
			Ensemble	***93.9***	***94.7***	***93.2***	***93.9***	***87.8***	***94.0***
			Hybrid	93.8	98.2	89.6	93.7	87.5	93.9
10	10	71.4	SVMs	91.6	100.0	83.8	91.2	83.2	91.9
			kNN	93.1	96.8	89.6	93.1	86.2	93.2
			Ensemble	93.6	94.7	92.5	93.6	87.2	93.6
			Hybrid	***94.1***	***98.6***	***89.9***	***94.1***	***88.2***	***94.3***
11	11	78.54	SVMs	91.7	99.6	84.4	91.4	83.5	92.0
			kNN	90.4	93.0	88.0	90.4	80.8	90.5
			Ensemble	***93.6***	***94.4***	***92.9***	***93.6***	***87.2***	***93.6***
			Hybrid	92.9	97.9	88.3	92.9	85.8	93.1
12	12	85.68	SVMs	91.7	99.6	84.4	91.4	83.5	92.0
			kNN	90.0	92.6	87.7	90.1	80.1	90.1
			Ensemble	***94.6***	***96.1***	***93.2***	***94.6***	***89.2***	***94.7***
			Hybrid	93.1	98.2	88.3	93.0	86.2	93.3
13	13	92.82	SVMs	91.7	99.6	84.4	91.4	83.5	92.0
			kNN	90.0	93.0	87.3	90.1	80.1	90.1
			Ensemble	***93.8***	***94.7***	***92.9***	***93.8***	***87.5***	***93.8***
			Hybrid	92.9	98.2	88.0	92.8	85.8	93.1
14	14	99.96	SVMs	91.9	99.6	84.7	91.6	83.9	92.2
			kNN	90.0	93.0	87.3	90.1	80.1	90.1
			Ensemble	***94.4***	***96.1***	***92.9***	***94.5***	***88.8***	***94.5***
			Hybrid	92.7	97.9	88.0	92.7	85.5	92.9

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Table 18 E Dataset Summary Table – Best Methods

L	FN	FP	Model	Accuracy	Sensitivity	Specificity	F1 Score	Kappa	AUC
1	1	7.14	SVMs	96.1	100.0	92.5	96.1	92.2	96.3
			kNN	97.3	100.0	94.8	97.3	94.6	97.4
			Ensemble	***97.5***	***100.0***	***95.1***	***97.5***	***94.9***	***97.6***
			Hybrid	97.3	100.0	94.8	97.3	94.6	97.4
2	2	14.28	SVMs	96.1	100.0	92.5	96.1	92.2	96.3
			kNN	96.8	98.9	94.8	96.8	93.6	96.9
			Ensemble	***97.1***	***98.9***	***95.5***	***97.2***	***94.3***	***97.2***
			Hybrid	96.8	98.9	94.8	96.8	93.6	96.9
3	3	21.42	***SVMs***	***96.1***	***100.0***	***92.5***	***96.1***	***92.2***	***96.3***
			kNN	95.6	95.8	95.5	95.6	91.2	95.6
			Ensemble	95.6	95.1	96.1	95.6	91.2	95.6
			Hybrid	95.4	95.8	95.1	95.5	90.9	95.5
4	4	28.56	***SVMs***	***96.1***	***100.0***	***92.5***	***96.1***	***92.2***	***96.3***
			kNN	95.4	95.4	95.5	95.4	90.9	95.4
			Ensemble	95.9	95.8	96.1	95.9	91.9	95.9
			Hybrid	95.4	95.8	95.1	95.5	90.9	95.5
5	5	35.7	***SVMs***	***96.1***	***100.0***	***92.5***	***96.1***	***92.2***	***96.3***
			kNN	95.3	95.4	95.1	95.3	90.5	95.3
			Ensemble	95.4	95.1	95.8	95.4	90.9	95.4
			Hybrid	95.3	95.8	94.8	95.3	90.5	95.3
6	6	42.84	***SVMs***	***96.1***	***100.0***	***92.5***	***96.1***	***92.2***	***96.3***
			kNN	95.6	96.5	94.8	95.6	91.2	95.6
			Ensemble	95.8	95.8	95.8	95.8	91.5	95.8
			Hybrid	95.6	96.8	94.5	95.6	91.2	95.7
7	7	49.98	***SVMs***	***96.3***	***100.0***	***92.9***	***96.3***	***92.6***	***96.4***
			kNN	95.4	95.8	95.1	95.5	90.9	95.5
			Ensemble	95.1	94.4	95.8	95.1	90.2	95.1
			Hybrid	95.3	96.1	94.5	95.3	90.5	95.3

Table 19 E Dataset Summary Table – Best Methods (Continue)

L	FN	FP	Model	Accuracy	Sensitivity	Specificity	F1 Score	Kappa	AUC
8	8	57.12	***SVMs***	***96.3***	***100.0***	***92.9***	***96.3***	***92.6***	***96.4***
			kNN	95.3	95.4	95.1	95.3	90.5	95.3
			Ensemble	95.4	95.1	95.8	95.4	90.9	95.4
			Hybrid	95.3	96.1	94.5	95.3	90.5	95.3
9	9	64.26	***SVMs***	***95.9***	***100.0***	***92.2***	***95.9***	***91.9***	***96.1***
			kNN	93.2	95.1	91.6	93.3	86.5	93.3
			Ensemble	94.9	95.4	94.5	94.9	89.9	95.0
			Hybrid	94.8	97.5	92.2	94.8	89.5	94.9
10	10	71.4	***SVMs***	***95.9***	***100.0***	***92.2***	***95.9***	***91.9***	***96.1***
			kNN	93.2	95.1	91.6	93.3	86.5	93.3
			Ensemble	94.8	95.1	94.5	94.8	89.5	94.8
			Hybrid	94.8	97.5	92.2	94.8	89.5	94.9
11	11	78.54	***SVMs***	***95.9***	***100.0***	***92.2***	***95.9***	***91.9***	***96.1***
			kNN	93.1	96.1	90.3	93.1	86.2	93.2
			Ensemble	95.4	96.1	94.8	95.5	90.9	95.5
			Hybrid	95.6	99.3	92.2	95.6	91.2	95.8
12	12	85.68	***SVMs***	***96.1***	***100.0***	***92.5***	***96.1***	***92.2***	***96.3***
			kNN	91.0	93.7	88.6	91.1	82.1	91.1
			Ensemble	95.8	97.5	94.2	95.8	91.6	95.8
			Hybrid	95.8	99.3	92.5	95.8	91.6	95.9
13	13	92.82	***SVMs***	***95.9***	***100.0***	***92.2***	***95.9***	***91.9***	***96.1***
			kNN	91.2	94.0	88.6	91.2	82.4	91.3
			Ensemble	95.9	97.9	94.2	96.0	91.9	96.0
			Hybrid	95.4	98.9	92.2	95.5	90.9	95.6
14	14	99.96	SVMs	95.8	99.6	92.2	95.8	91.6	95.9
			kNN	91.6	94.7	88.6	91.6	83.1	91.7
			Ensemble	***96.5***	***98.9***	***94.2***	***96.5***	***92.9***	***96.5***
			Hybrid	95.8	99.6	92.2	95.8	91.6	95.9

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Table 20 F Dataset Dataset Summary Table – Best Methods

L	FN	FP	Model	Accuracy	Sensitivity	Specificity	F1 Score	Kappa	AUC
1	1	7.14	SVMs	98.8	100.0	97.7	98.9	97.6	98.9
			kNN	***99.2***	***100.0***	***98.4***	***99.2***	***98.3***	***99.2***
			Ensemble	77.7	54.9	98.7	70.6	54.6	76.8
			Hybrid	***99.2***	***100.0***	***98.4***	***99.2***	***98.3***	***99.2***
2	2	14.28	SVMs	98.8	100.0	97.7	98.9	97.6	98.9
			kNN	99.0	100.0	98.1	99.0	98.0	99.0
			Ensemble	***99.3***	***100.0***	***98.7***	***99.3***	***98.6***	***99.4***
			Hybrid	99.0	100.0	98.1	99.0	98.0	99.0
3	3	21.42	SVMs	98.8	100.0	97.7	98.9	97.6	98.9
			kNN	98.8	99.6	98.1	98.8	97.6	98.8
			Ensemble	***99.2***	***99.6***	***98.7***	***99.2***	***98.3***	***99.2***
			Hybrid	98.8	99.6	98.1	98.8	97.6	98.8
4	4	28.56	SVMs	98.8	100.0	97.7	98.9	97.6	98.9
			kNN	98.8	99.6	98.1	98.8	97.6	98.8
			Ensemble	***99.2***	***99.6***	***98.7***	***99.2***	***98.3***	***99.2***
			Hybrid	98.8	99.6	98.1	98.8	97.6	98.8
5	5	35.7	SVMs	98.8	100.0	97.7	98.9	97.6	98.9
			kNN	98.8	99.6	98.1	98.8	97.6	98.8
			Ensemble	***99.0***	***99.3***	***98.7***	***99.0***	***98.0***	***99.0***
			Hybrid	98.8	99.6	98.1	98.8	97.6	98.8
6	46	42.84	SVMs	98.8	100.0	97.7	98.9	97.6	98.9
			kNN	98.6	99.6	97.7	98.7	97.3	98.7
			Ensemble	***99.0***	***99.3***	***98.7***	***99.0***	***98.0***	***99.0***
			Hybrid	98.6	99.6	97.7	98.7	97.3	98.7
7	7	49.98	***SVMs***	***98.8***	***100.0***	***97.7***	***98.9***	***97.6***	***98.9***
			kNN	98.6	99.6	97.7	98.7	97.3	98.7
			Ensemble	98.5	99.3	97.7	98.5	97.0	98.5
			Hybrid	98.6	99.6	97.7	98.7	97.3	98.7

Table 21 F Dataset Summary Table – Best Methods (Continue)

L	FN	FP	Model	Accuracy	Sensitivity	Specificity	F1 Score	Kappa	AUC
8	8	57.12	***SVMs***	***98.6***	***99.6***	***97.7***	***98.7***	***97.3***	***98.7***
			kNN	98.3	98.9	97.7	98.3	96.6	98.3
			Ensemble	97.6	97.5	97.7	97.6	95.3	97.6
			Hybrid	98.5	99.3	97.7	98.5	97.0	98.5
9	9	64.26	SVMs	98.6	99.6	97.7	98.7	97.3	98.7
			kNN	97.5	97.5	97.4	97.5	94.9	97.5
			Ensemble	***99.0***	***99.3***	***98.7***	***99.0***	***98.0***	***99.0***
			Hybrid	98.5	99.3	97.7	98.5	97.0	98.5
10	10	71.4	SVMs	98.6	99.6	97.7	98.7	97.3	98.7
			kNN	97.5	97.5	97.4	97.5	94.9	97.5
			Ensemble	***99.0***	***99.3***	***98.7***	***99.0***	***98.0***	***99.0***
			Hybrid	98.5	99.3	97.7	98.5	97.0	98.5
11	11	78.54	SVMs	98.6	99.6	97.7	98.7	97.3	98.7
			kNN	97.3	98.9	95.8	97.3	94.6	97.4
			Ensemble	***99.2***	***99.6***	***98.7***	***99.2***	***98.3***	***99.2***
			Hybrid	98.8	100.0	97.7	98.9	97.6	98.9
12	12	85.68	SVMs	98.5	99.3	97.7	98.5	97.0	98.5
			kNN	96.3	97.2	95.5	96.3	92.6	96.3
			Ensemble	***99.2***	***99.6***	***98.7***	***99.2***	***98.3***	***99.2***
			Hybrid	98.8	100.0	97.7	98.9	97.6	98.9
13	13	92.82	SVMs	98.5	99.3	97.7	98.5	97.0	98.5
			kNN	96.6	97.9	95.5	96.7	93.2	96.7
			Ensemble	98.0	97.2	98.7	97.9	95.9	97.9
			Hybrid	***98.8***	***100.0***	***97.7***	***98.9***	***97.6***	***98.9***
14	14	99.96	SVMs	98.6	99.6	97.7	98.7	97.3	98.7
			kNN	96.8	98.2	95.5	96.8	93.6	96.8
			Ensemble	98.3	97.9	98.7	98.3	96.6	98.3
			Hybrid	***98.8***	***100.0***	***97.7***	***98.9***	***97.6***	***98.9***

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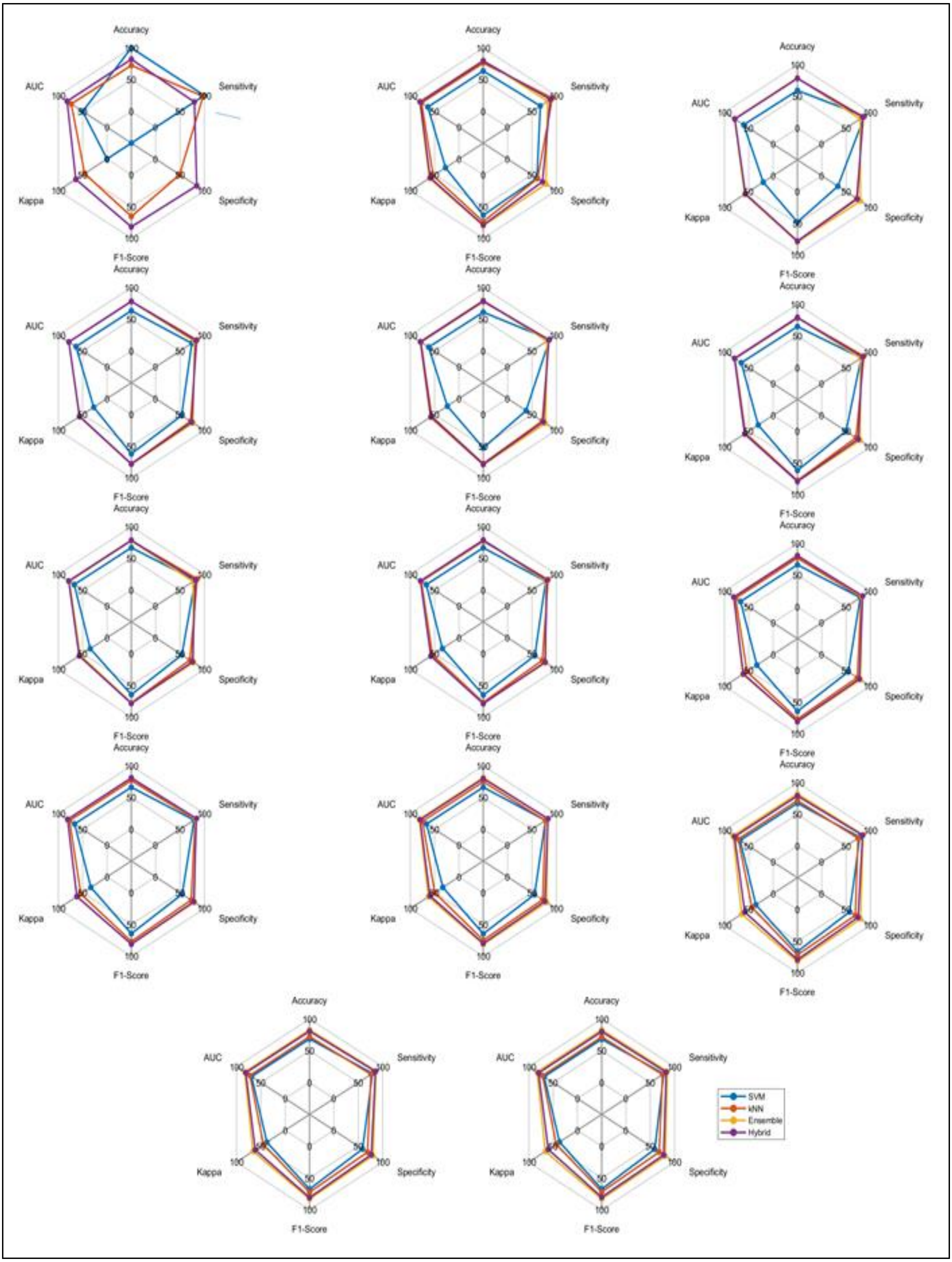

Fig 6 Performance of All Classification Models on A Dataset

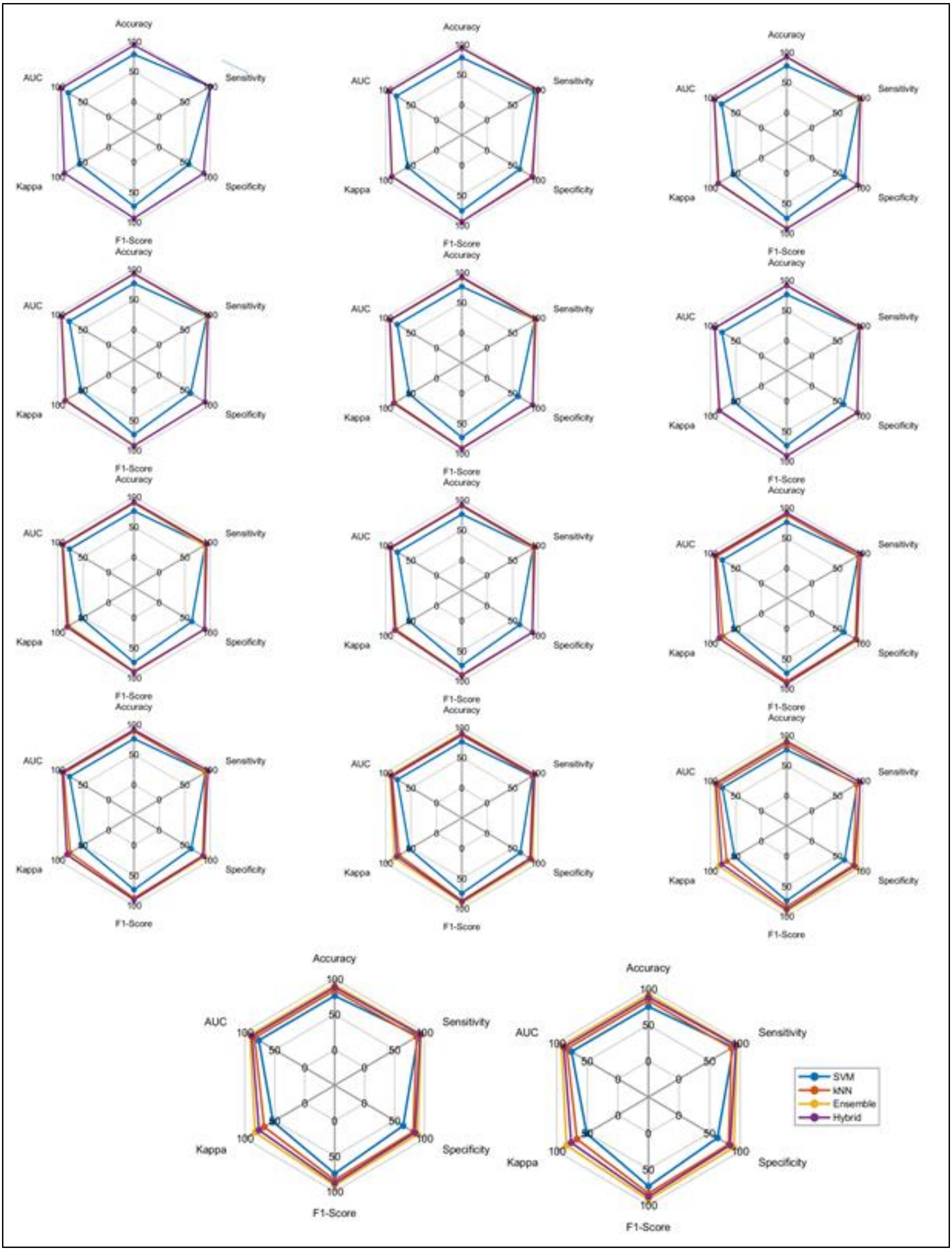

Fig 7 Performance of All Classification Models on B Dataset

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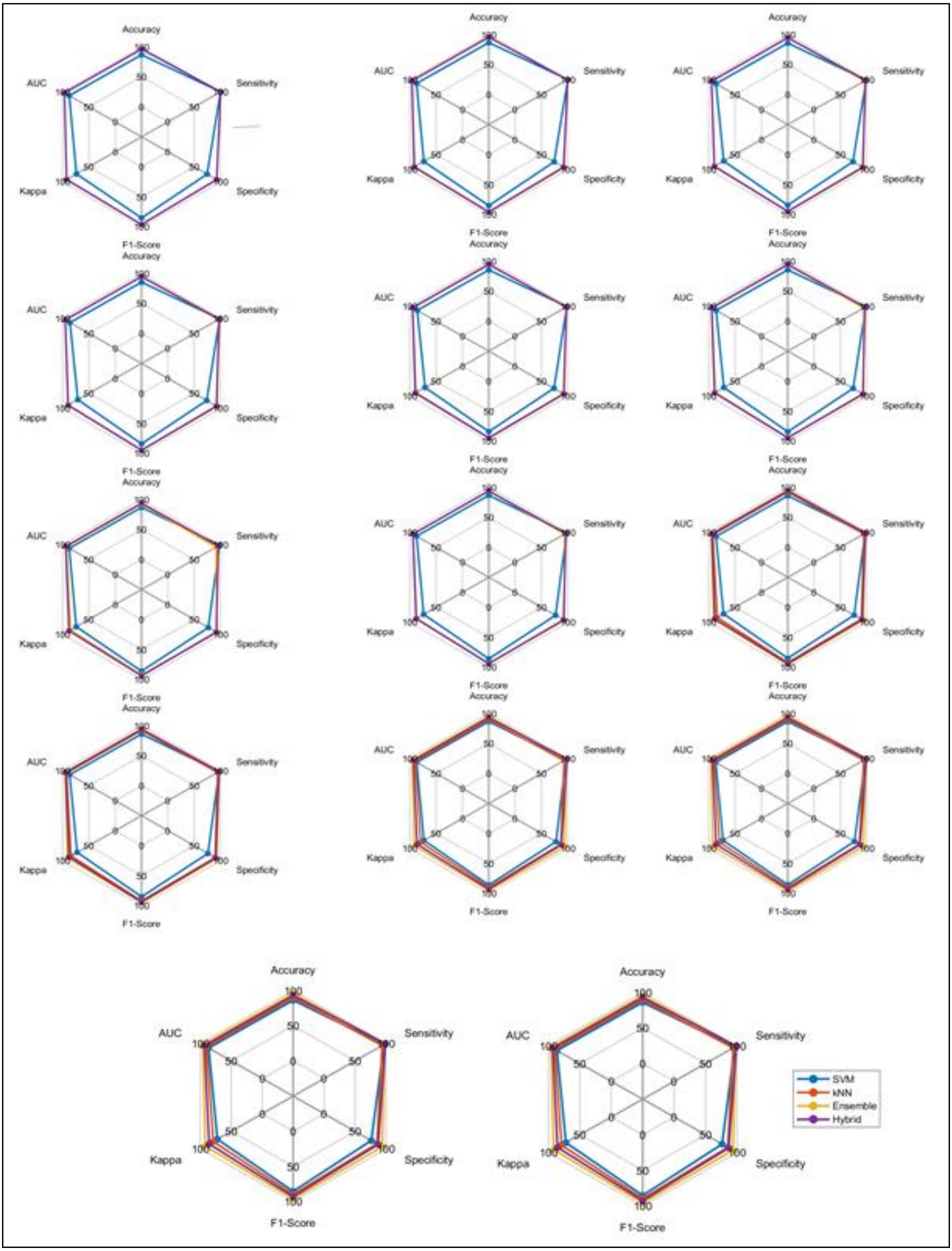

Fig 8 Performance of All Classification Models on C Dataset

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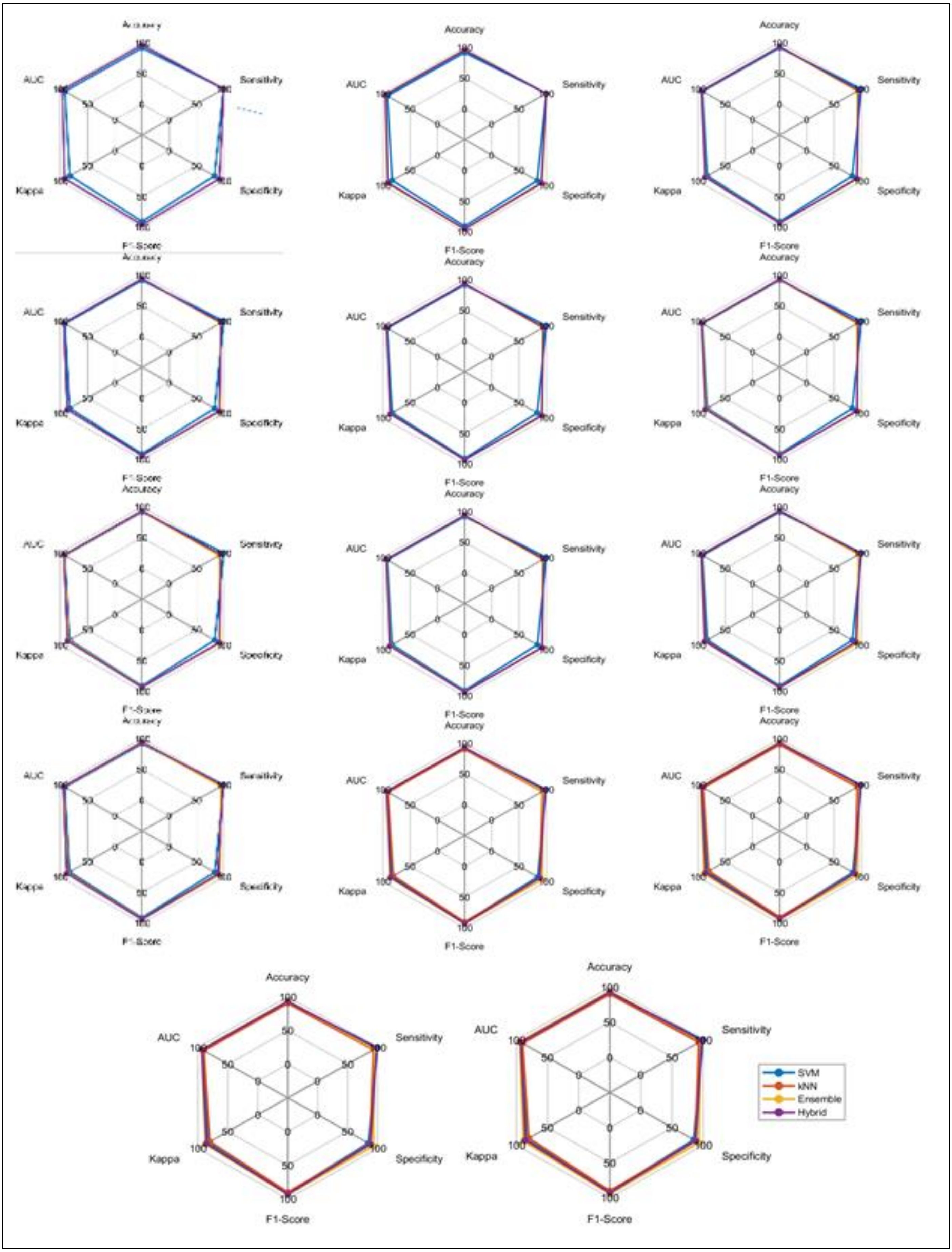

Fig 9 Performance of All Classification Models on D Dataset

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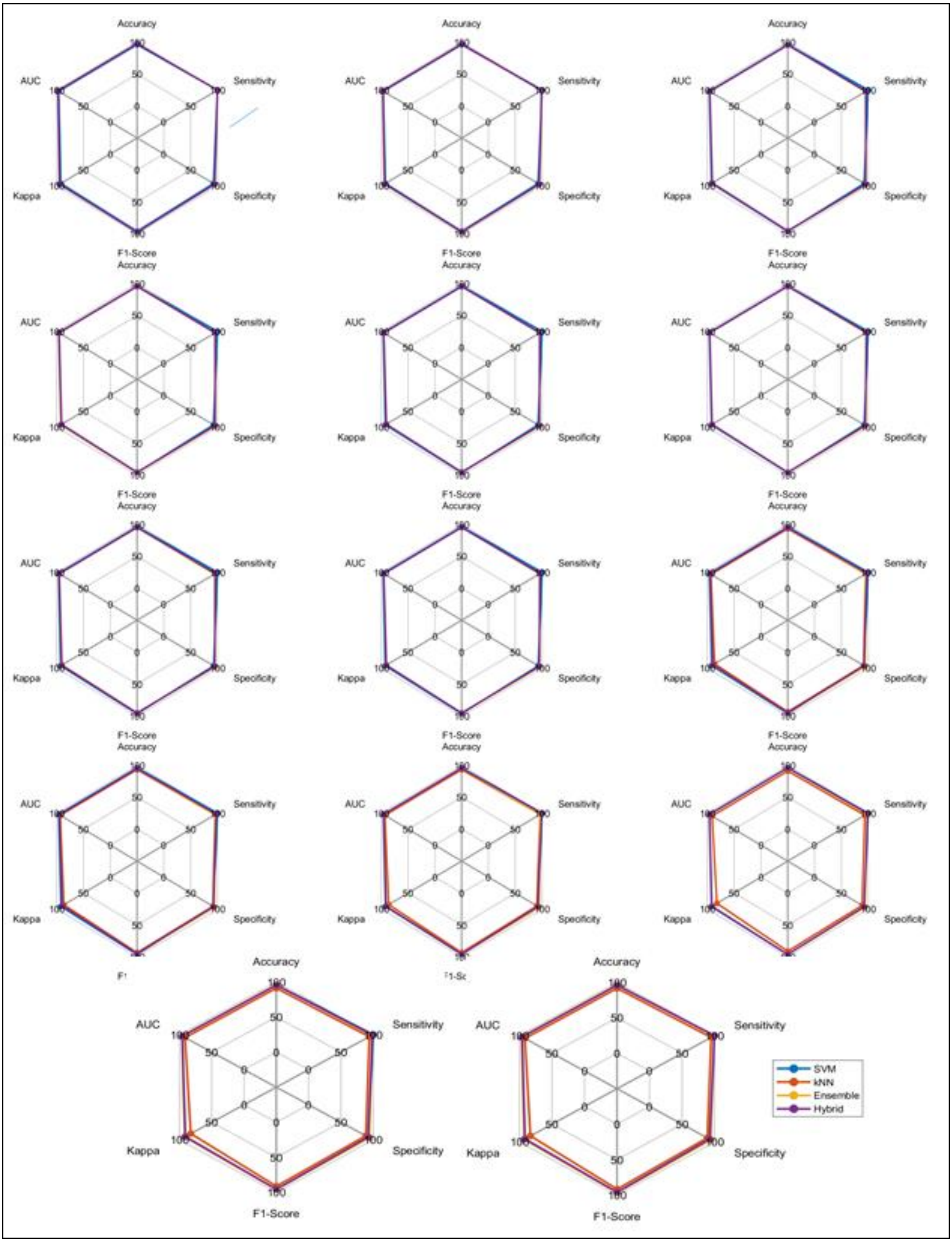

Fig 10 Performance of All Classification Models on E Dataset

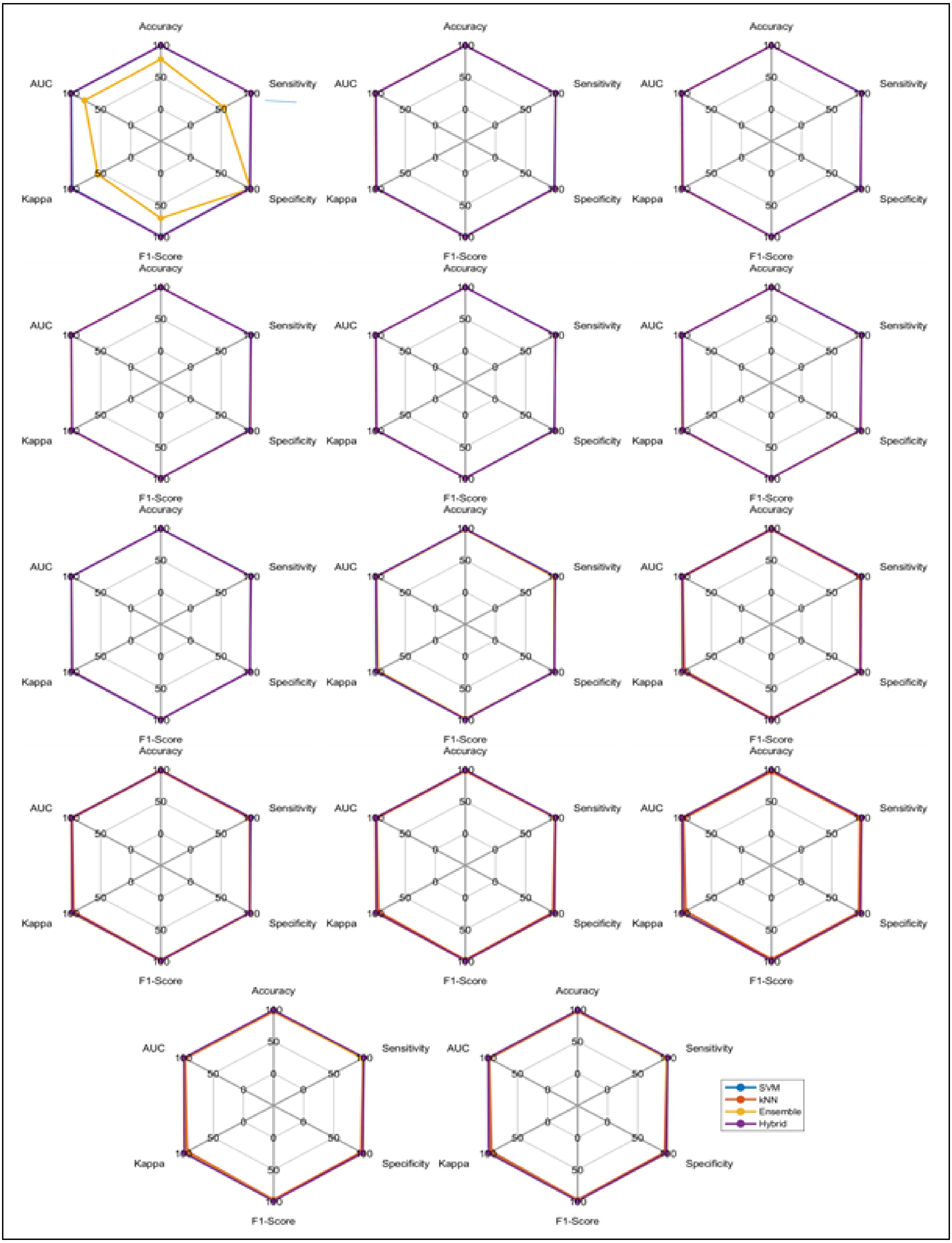

Fig 11 Performance of All Classification Models on F Dataset

IV. DISCUSSION

In our study, classification methods such as Ensemble, kNN, SVMs, and Hybrid Artificial Intelligence were applied within the scope of machine learning. Based on the results obtained, a breast cancer diagnosis algorithm was developed. The literature reveals that various studies have employed different machine learning and feature selection algorithms to work on datasets with different characteristics for breast cancer diagnosis.

In the literature, various machine learning techniques have been utilized, including Artificial Neural Network (ANN), Support Vector Machines (SVMs), Naive Bayes (NB), Classification and Regression Tree (CART), k-Nearest Neighbors (kNN), Linear Regression (LR), Multilayer Perceptron (MLP), Random Forest, Extreme Boost, Decision Tree (C4.5), Logistic Regression, Linear Discriminant Analysis, Boosting and AdaBoost, Bagging Algorithm, IBk (Instance-based learning with certain parameters), and Random Committee Algorithm.

In the literature, various performance metrics have been employed to evaluate the performance of machine learning models. These include F-Measure, AUC (Area Under the ROC Curve), ROC (Receiver Operating Characteristic) curve, accuracy, recall, sensitivity, specificity, kappa statistics, TP Rate (True Positive Rate), FP Rate (False Positive Rate), MCC (Matthews Correlation Coefficient), Area Under the Receiver Operating Characteristics, time complexity, Lift Curve, Calibration Plot, and techniques like Recursive Feature Elimination.

In our study, performance evaluation criteria similar to those used in the literature, such as accuracy, specificity, sensitivity, kappa statistic, F-Measure, and AUC, were also applied [27], [28].

In our study, the highest accuracy rate was achieved using the Ensemble method at 99.3%, the highest specificity rate was also obtained with the Ensemble method at 98.7%, and the highest sensitivity rate was found to be 100% across multiple methods.

In the literature, machine learning algorithms have been developed on various platforms such as R programming, Weka, Spark, and Python [47], [48], [49]. The machine learning algorithms implemented on these platforms have been observed to be less effective compared to those used in this study.

In contrast to our study, the majority of studies in the literature have been conducted using the Wisconsin Diagnostic Breast Cancer (WDBC) dataset [50], [51], [52].

In the literature, only one study used the same dataset as our research [29].

Other studies, however, were conducted on datasets different from the Wisconsin dataset [53], [54].

Similar to our study, some works in the literature have employed common stages such as creating subsets by reducing features, data cleaning, feature selection, and feature extraction. However, these studies did not achieve high accuracy rates [55], [56], [57].

In the literature, some studies have divided the dataset into 80% training and 20% testing. Similar to these studies, many others have created subsets by reducing features and conducted feature selection [31]. In another study, the training and testing datasets were split 66% to 33%, where SVMs achieved the best accuracy performance with 96.9957% [34]. However, despite most models in the literature achieving accuracy rates above 90%, the highest accuracy rate found in our study, using a 50% training and 50% testing split, did not exceed 99.3% with the Ensemble method. The highest accuracy rates in our study were 99.2% with the kNN method, 98.8% with the SVMs method, and 99.2% with the Hybrid method.

In another study from the literature, the highest specificity rate was found to be 99.07% and the highest sensitivity rate was 98.41% [30]. However, in our study, the highest specificity rate was 98.7%, while the highest sensitivity rate reached 100%.

In another study from the literature, the highest AUC value was 99.5% using the SVMs method, while in our study, the AUC value was 99.4% with the Ensemble method [57]. Regarding the F1 score, the highest value in the literature was 98.1% using the SVMs method, whereas in our study, the highest F1 score was found to be 99.3% with the Ensemble method [57].

In studies that used the same dataset and similar machine learning algorithms as in our research, the highest accuracy rate was found to be 82.70% using the Random Forest method, the highest specificity rate was 84% using the SVMs method, and the highest sensitivity rate was 84% using the Extreme Boost method [29].

When reviewing all studies, it is observed that most performance criteria in machine learning models do not exceed 99.68% accuracy [26]. Comparing the study with the highest accuracy rate in the literature to our work, the accuracy rate of 99.68% achieved using the SVMs algorithm in a Spark environment is higher than any accuracy rate in our study. However, in the study that employed deep learning techniques such as CNN, SAE, and SSAE, only one of the four machine learning algorithms used in our study produced a lower accuracy rate. The remaining three machine learning algorithms in our study outperformed the accuracy rates of the deep learning techniques used in the literature [51].

In a study from the literature that applied similar stages such as feature selection and feature extraction techniques to ANN, SVMs, and NB for breast cancer, the highest specificity rate was found to be 99.07%, and the highest sensitivity rate was 98.41%. These values represent the highest specificity and sensitivity rates reported in the literature for breast cancer research [30]. However, in our study, the highest specificity rate was found to be 98.7%, and the sensitivity rate reached 100%. These results demonstrate that our study is a reliable approach for detecting both diseased and healthy individuals in breast cancer diagnosis.

In a study comparing six different machine learning techniques—CART, SVMs, NB, kNN, LR, and MLP— for breast cancer diagnosis, the dataset was split into 80% training and 20% testing. Similar to our study, some studies have also created subsets by reducing features and performing feature selection [31]. However, despite most models in the literature achieving accuracy rates above 90%, the highest accuracy rate found in our study, using a 50% training and 50% testing split, did not exceed 99.3% with the Ensemble method. This indicates that our study is more applicable and suitable for use in the healthcare field.

In some studies, the same dataset used in our research was also employed, along with similar machine learning algorithms. In these studies, the highest accuracy rate was found to be 82.70% with the Random Forest method, the highest specificity rate was 84% with the SVMs method, and the highest sensitivity rate was 84% with the Extreme Boost method [29]. In contrast, the results from our study showed the highest accuracy rate of 99.3%, the highest specificity rate of 98.7%, both achieved with the Ensemble method, and the highest sensitivity rate of 100% with multiple methods. This demonstrates that our study can achieve higher accuracy, specificity, and sensitivity rates with different machine learning techniques. Consequently, it reinforces the reliability of our study in detecting both diseased and healthy individuals in breast cancer diagnosis, indicating its applicability and suitability for use in the healthcare field.

In another study, ANN and SVMs were used for breast cancer classification prediction, implemented using WEKA. The training and testing datasets were split 66% to 33%. The experimental results showed that SVMs achieved the best accuracy performance at 96.9957% [34]. Despite being conducted on a different platform, with fewer machine learning algorithms and different training and testing percentages, the study did not achieve an accuracy rate close to the highest value of 99.3% found in our study, where a 50% training and 50% testing split was applied. This suggests that the approach in our study could yield superior results in the healthcare field.

In another study, machine learning algorithms such as Random Forest (RF), Naive Bayes (NB), SVMs, and kNN were used. After applying feature selection and extraction, these algorithms were implemented using the WEKA program, with the dataset labels classified as benign and malignant. However, due to missing values, the number of data points in the dataset was reduced. Similar to our study, this research applied data reduction techniques due to data imbalance and used comparable machine learning algorithms and approaches. Nevertheless, the highest accuracy rates achieved were 97.9% with the SVMs method, 96% with the RF method, 92.6% with the Naive Bayes method, and 96.1% with the kNN method [32]. In contrast, our study achieved higher accuracy rates: 99.3% with the Ensemble method, 99.2% with the kNN method, 98.8% with the SVMs method, and 99.2% with the Hybrid method. This demonstrates that our study outperforms similar studies in the literature, particularly in the healthcare field.

In another study, machine learning algorithms such as SVMs, C4.5, NB, and kNN were used. Each algorithm was evaluated in terms of accuracy, precision, sensitivity, and specificity. The highest accuracy rate was observed with SVMs at 97.13%, while the accuracy rates for C4.5, NB, and kNN ranged between 95.12% and 95.28%. All the applications in this study were conducted using the WEKA data mining tool [33]. In our study, which examined similar algorithms using Matlab, the highest accuracy rates were 99.3% with the Ensemble method, 99.2% with the kNN method, 98.8% with the SVMs method, and 99.2% with the Hybrid method. This indicates that despite using similar algorithms, our study achieved higher accuracy rates on a different platform. Consequently, this demonstrates that the algorithms used in our study performed better in terms of accuracy, and it also suggests that our research is more effective in the healthcare field compared to the mentioned study in the literature.

In a different study from the literature, three machine learning techniques—SVMs, Random Forest (RF), and Bayesian Networks (BN)—were applied and compared. These techniques were evaluated based on accuracy, recall, precision, and the area under the ROC curve. The entire study was conducted using the WEKA environment, and the highest accuracy rate achieved was 97% [35]. In contrast, our study, conducted in the Matlab environment, achieved a higher accuracy rate of 99.3%. This result suggests that our study may provide more reliable outcomes in breast cancer diagnosis compared to the mentioned study.

In a study from the literature, machine learning techniques such as C4.5, SVMs, and ANN were applied and evaluated in terms of accuracy, specificity, and sensitivity. The analysis results showed that the accuracy values for DT, ANN, and SVMs were 93.6%, 94.7%, and 95.7%, respectively [53]. In contrast, our study, which examined similar algorithms, achieved higher accuracy rates: 99.3% with the Ensemble method, 99.2% with the kNN method, 98.8% with the SVMs method, and 99.2% with the Hybrid method. Despite the various machine learning techniques applied in the literature, none of them surpassed the accuracy values obtained in our study. This indicates that the machine learning techniques used in our research could yield more reliable results, particularly in breast cancer diagnosis.

In another study from the literature, machine learning algorithms such as RF, kNN, and NB were used. Conducted in the Python environment, this study compared machine learning algorithms based on accuracy, precision, and F1-Score parameters. The results showed that the highest accuracy was achieved with the kNN method at 95.9%, the highest precision with kNN at 98.27%, the highest recall with RF at 93.65%, and the highest F1-Score with kNN at 94.2%. The accuracy rates for RF and NB were 94.74% and 94.47%, respectively [47]. In our study, while the machine learning

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algorithms and methods applied are similar to those in the mentioned study, our research was conducted in a different platform, specifically Matlab. Despite these similarities, our study achieved superior results, with the highest accuracy rates being 99.3% with the Ensemble method, 99.2% with the kNN method, 98.8% with the SVMs method, and 99.2% with the Hybrid method. Additionally, the highest F1-Score was 99.2% with the Ensemble method. These results indicate that our study has obtained more efficient outcomes compared to the mentioned study, particularly in the diagnosis of breast cancer, demonstrating the potential for superior results in this critical area.

In a study comparing machine learning algorithms such as SVMs, C4.5, Naive Bayes (NB), and kNN, each algorithm was evaluated in terms of accuracy, precision, sensitivity, and specificity. The highest accuracy rate was found to be 97.13% with the SVMs method. The accuracy rates for C4.5, Naive Bayes, and kNN varied between 95.12% and 95.28%. All applications were conducted using WEKA data mining [50]. In contrast, the results obtained in our study, conducted in the Matlab environment, showed higher performance: the highest accuracy rate was 99.3% with the Ensemble method, the highest specificity rate was 98.7% with the Ensemble method, and the highest sensitivity rate was 100% across multiple methods. This demonstrates that our study, using similar machine learning techniques, achieved higher percentages of accuracy, specificity, and sensitivity. It also indicates that our research has the lowest error rate in breast cancer diagnosis and the highest capacity for accurate classification.

The primary objective of the study in the literature was to review various data mining and machine learning algorithms used for breast cancer prediction. The focus was on identifying the most suitable algorithm with the highest accuracy for breast cancer diagnosis. The study examined linear algorithms (e.g., Logistic Regression, Linear Discriminant Analysis), nonlinear algorithms (e.g., CART, Naive Bayes, kNN, SVMs), and ensemble algorithms (e.g., Ctree, Random Forest, Boosting, AdaBoost). A comparative analysis of each algorithm's accuracy was performed, and the most appropriate machine learning algorithms for breast cancer diagnosis were identified. It was found that different techniques were suitable under different conditions and datasets. Among all machine learning algorithms compared, SVMs emerged as the most appropriate for breast cancer prediction, achieving the highest accuracy of 98.03% in WEKA and 99.68% in Spark. Additionally, when applied to a different dataset collected from another database, deep learning techniques such as CNN, SAE, and SSAE achieved an accuracy rate of 98.9% \cite{Fatima2020}. In comparison, our study was conducted in Matlab, similar to the platforms used in the literature, and employed comparable algorithms such as Ensemble, kNN, SVMs, and Hybrid. The accuracy rates in our study were 99.3% with the Ensemble method, 99.2% with the kNN method, 98.8% with the SVMs method, and 99.2% with the Hybrid method. When comparing our study with the literature, it is observed that the highest accuracy rate achieved in the literature using the SVMs algorithm in the WEKA environment was 99.68%, which is higher than the accuracy rates achieved in our study. However, when considering the study that applied deep learning techniques like CNN, SAE, and SSAE, only one of the four machine learning algorithms used in our study achieved a lower accuracy rate than the deep learning techniques. The remaining three algorithms in our study outperformed the accuracy rates achieved by these deep learning techniques. This suggests that, in the context of breast cancer diagnosis, the study from the literature is somewhat more successful than our own, particularly when using the SVMs algorithm in a different environment. However, our study demonstrated superiority over the literature that employed deep learning techniques, indicating that our approach remains reliable and effective for breast cancer diagnosis. Despite this, it is important to acknowledge that there is still a study in the literature that has outperformed ours in terms of accuracy.

In a different study from the literature, data mining algorithms such as the Bagging Algorithm, IBk, Random Committee Algorithm, Random Forest Algorithm, and Simple Classification and Regression Tree (Simple CART Algorithm) were used for the diagnosis and prediction of breast cancer. The results were analyzed in the WEKA program using Bayes, Function, Meta, Lazy, Trees, and other perspectives. The analysis revealed that the Random Forest Algorithm had the highest accuracy level, making it the most suitable algorithm for breast cancer diagnosis. The accuracy rate for the Random Forest algorithm was found to be 92.2%, while the Bagging, IBk, and Random Committee Algorithms achieved accuracy rates of 90.9%, 90%, and 90.9%, respectively [48]. In contrast, our study conducted in the Matlab environment differed in terms of the machine learning algorithms and methods applied compared to the aforementioned study. The highest accuracy rates achieved in our study were 99.3% with the Ensemble method, 99.2% with the kNN method, 98.8% with the SVMs method, and 99.2% with the Hybrid method. These results indicate that our study utilized more suitable machine learning algorithms, yielding more efficient outcomes when compared to the literature. This demonstrates that our research is superior in terms of the algorithms and methods applied for breast cancer diagnosis.

In another study from the literature, SVMs, Ctree, and Random Forest algorithms were used for classifying nine models in the diagnosis of breast cancer. The dataset was processed using two different data mining tools, WEKA and Spark, where the accuracy and error rates of the algorithms were compared. The study filtered two datasets (GE and DM) to obtain genes primarily responsible for the presence of tumors. The comparisons between the algorithms in both tools revealed that SVMs had the highest accuracy among the algorithms, with an accuracy rate of 99.68% in Spark and 98.03% in WEKA [26]. In contrast, our study utilized machine learning algorithms in the Matlab environment rather than data mining tools. Despite employing similar algorithms, such as SVMs, our study achieved the highest accuracy rates of 99.3% with the Ensemble method, 99.2% with the kNN method, 98.8% with the SVMs method, and 99.2% with the Hybrid method. When comparing the accuracy rates of this high-accuracy study in the literature to those in our study, it is evident that while some algorithms in the literature surpassed

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those in our study, overall, our research demonstrated a higher potential for accurately diagnosing breast cancer. This suggests that the methods used in our study could offer more reliable results in breast cancer diagnosis.

In a study aligned with our research, the NB, kNN, and J48 algorithms were used to predict nine different types of breast cancer. The study initially compared symptoms based on the training dataset to test the accuracy of the results, with matching symptoms indicating correctness. Throughout this process, different types of breast cancer were predicted, and each algorithm was classified based on accuracy rates. It was found that the accuracy rates of NB and kNN were higher than that of the J48 decision tree classifier, with accuracy values of 98.2%, 98.8%, and 98.5%, respectively [54]. In our study conducted in the Matlab environment, despite using similar machine learning algorithms like kNN, the highest accuracy rates achieved were 99.3% with the Ensemble method, 99.2% with the kNN method, 98.8% with the SVMs method, and 99.2% with the Hybrid method. This indicates that the findings in our study could lead to higher detection rates of breast cancer, suggesting a more effective approach in the healthcare field for identifying breast cancer with greater accuracy.

In the literature, a study focused on breast cancer diagnosis utilized a predictive machine learning model based on SVMs with a recursive feature elimination technique. The goal of the study was to select the correct features from a dataset of individuals with benign and malignant tumors. The recursive feature elimination technique was employed to evaluate the SVMs algorithm, and the performance matrix was designed to check the accuracy of the predictive SVMs model across different kernel types. The study reported an accuracy of 99% with the linear kernel, 98% with the RBF kernel, 97% with the polynomial kernel, and 84% with the sigmoid kernel [55]. In our study conducted in the Matlab environment, despite using a similar machine learning algorithm like SVMs, the highest accuracy rates achieved were 99.3% with the Ensemble method, 99.2% with the kNN method, 98.8% with the SVMs method, and 99.2% with the Hybrid method. When comparing the SVMs results specifically, the literature reported a slightly higher accuracy with the SVMs method. However, when evaluating the overall system, all other machine learning algorithms in our study outperformed those in the mentioned study. This suggests that our study may provide more reliable and accurate results in the healthcare field, particularly in breast cancer diagnosis, indicating the potential for better detection and classification outcomes.

In a different study from the literature, an effective model for early-stage breast cancer detection was proposed. The BCD model in the literature aimed to address data-related problems and improve classifier performance using a 10-fold cross-validation technique with SVMs. Various evaluation metrics, such as F1 measure, class accuracy, ROC Curve, AUC, Lift Curve, and Calibration Plot, were used, and models like AdaBoost, Random Forest, and Naïve Bayes were applied. The proposed BCD model achieved the highest accuracy of 98.1% and an AUC value of 0.995 among all applied models [57]. In our study, conducted in the Matlab environment, different machine learning algorithms were used, but similar evaluation metrics such as accuracy, F1 Score, and AUC were employed. When comparing these metrics, the highest accuracy rate in the literature was 98.1% with the SVMs method, while our study achieved 99.3% with the Ensemble method, 99.2% with the kNN method, 98.8% with the SVMs method, and 99.2% with the Hybrid method. For the AUC value, the literature reported the highest rate of 99.5% with the SVMs method, whereas our study found 99.4% with the Ensemble method. Regarding the F1 Score, the highest rate in the literature was 98.1% with the SVMs method, compared to 99.3% with the Ensemble method in our study. Although the AUC value in the literature was slightly higher than in our study, our research demonstrated higher F1 and accuracy values. This indicates that while the literature's model might be reliable in predicting breast cancer based on the AUC value, the F1 and accuracy values can vary. When comparing these common evaluation metrics, our study shows higher performance and suggests that more reliable results can be obtained in breast cancer diagnosis.

In a study from the literature, a new Nested Ensemble (NE) technique was used for breast cancer detection. This study created four two-layered Nested Ensemble classifiers based on voting and stacking techniques, named SV-BayesNet-2-MetaClassifier, SV-Naive Bayes-2-MetaClassifier, SV-BayesNet-3-MetaClassifier, and SV-Naive Bayes-3-MetaClassifier. In addition to these four classifiers, BayesNet and Naive Bayes (NB) classifiers were also evaluated. The performance of these classifiers was assessed using typical metrics such as accuracy, precision, recall, and ROC Curve. All experiments were conducted using the open-source machine learning software WEKA 3.9.1. The results showed that the highest accuracy for the BayesNet algorithm was 95.25% with an F1 score of 95.30%, while the NB algorithm achieved a maximum accuracy of 93.32% with an F1 score of 93.30%. The SV-BayesNet-2-MetaClassifier and SV-Naive Bayes-2-MetaClassifier both reached a maximum accuracy of 97.72% with an F1 score of 97.70%. The SV-BayesNet-3-MetaClassifier and SV-Naive Bayes-3-MetaClassifier both achieved the highest accuracy of 98.07% with an F1 score of 98.10% [52]. In our study conducted in the Matlab environment, different machine learning algorithms were used, yet similar evaluation metrics such as accuracy and F1 Score were applied. When comparing these metrics, the highest accuracy rate in the literature was 98.07%, whereas in our study, the highest accuracy rates were 99.3% with the Ensemble method, 99.2% with the kNN method, 98.8% with the SVMs method, and 99.2% with the Hybrid method. Regarding the F1 Score, the highest value in the literature was 98.1%, while in our study, the highest F1 Score was 99.3% with the Ensemble method. These comparisons show that the F1 and accuracy values in the literature are significantly lower than those obtained in our study. Therefore, when examining common metrics like F1 and accuracy, it is evident that our study can achieve more reliable and accurate results in breast cancer diagnosis.

In a different study from the literature, data mining tools were used for breast cancer prediction. The primary focus of

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the study was to classify algorithms such as Naive Bayes (NB), Bayesian Logistic Regression, Simple CART, and J48 based on accuracy and time complexity. The analysis conducted in the WEKA environment found the highest accuracy rates as follows: 95.27% with the NB method, 65.42% with Bayesian Logistic Regression, 98.13% with Simple CART, and 97.27% with the J48 method [58]. In our study, conducted in Matlab, completely different algorithms were used, resulting in higher accuracy rates: 99.3% with the Ensemble method, 99.2% with the kNN method, 98.8% with the SVMs method, and 99.2% with the Hybrid method. As a result, all algorithms used in our study achieved accuracy rates higher than those reported in the literature. This demonstrates that our research offers a more suitable approach for breast cancer diagnosis in the healthcare field.

In a different study from the literature, five non-linear machine learning algorithms—MLP, kNN, CART, SVMs, and Gaussian NB—were compared for breast cancer detection. The study's primary objective was to evaluate the effectiveness of these algorithms in terms of accuracy, precision, and recall for breast cancer detection. The accuracy rates of all algorithms were analyzed, with MLP achieving the highest accuracy of 99.12%, outperforming kNN, CART, NB, and SVMs. The accuracy rates for the other algorithms were 95.61% with kNN, 93.85% with CART, 94.73% with NB, and 98.24% with SVMs [59]. In our study conducted in Matlab, similar algorithms like kNN and SVMs were used, achieving higher accuracy rates: 99.3% with the Ensemble method, 99.2% with kNN, 98.8% with SVMs, and 99.2% with the Hybrid method. These results indicate that our study achieved higher accuracy values for similar machine learning techniques like kNN and SVMs. This demonstrates that our research can potentially provide more precise results in breast cancer diagnosis within medical applications.

In another study from the literature, researchers conducted a comparative analysis of NB, Random Forest, Logistic Regression, MLP, and kNN for breast cancer prediction. The evaluation of all these algorithms was conducted based on metrics such as Kappa Statistics, TP Rate, FP Rate, Precision, Recall, F-Measure, MCC, and ROC Area, focusing on the accuracy of each algorithm. Each algorithm was applied to the dataset to analyze its accuracy. The accuracy rates for kNN, NB, and Random Forest were 72.3%, 71.6%, and 69.5%, respectively, while Logistic Regression and MLP achieved accuracy rates of 68.8% and 64.6%, respectively. In terms of F-Measure, the values for kNN, NB, and Random Forest were 69.7%, 71.7%, and 66.9%, while Logistic Regression and MLP achieved F-Measure values of 67.5% and 64.7%, respectively [49]. In our study conducted in Matlab, similar machine learning algorithms like kNN were used, along with similar evaluation metrics such as accuracy and F1 Score. When comparing all parameters, the highest accuracy rate in the literature was 72.3% with kNN, whereas in our study, the highest accuracy rates were 99.3% with the Ensemble method, 99.2% with kNN, 98.8% with SVMs, and 99.2% with the Hybrid method. In terms of F1 Score, the highest value in the literature was 71.7%, while in our study, the highest F1 Score was 99.3% with the Ensemble method. When comparing the commonly used accuracy and F1 values between our study and the literature, it is evident that the values in our study are significantly higher. This indicates that our research has the potential to achieve a higher performance in breast cancer prediction.

When all these results are compared, our study demonstrates that it can achieve higher percentages of accuracy, specificity, and sensitivity using different machine learning techniques. This reinforces the reliability of our study in accurately identifying both diseased and healthy individuals in breast cancer diagnosis, highlighting its suitability and applicability in the healthcare field as a more effective and practical approach.

- *Conflict of Interest*

The authors declare that there is no conflict of interest.

- *Financial Support*

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