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RESEARCH ARTICLE

A Novel Web Framework for Cervical Cancer Detection System: A Machine Learning Breakthrough

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ABSTRACT Cervical cancer, the second most prevalent cancer among women worldwide, is primarily attributed to the human papillomavirus (HPV). Despite advances in healthcare, it remains a significant cause of mortality among women across diverse regions, surpassing other hereditary cancers. Early detection is pivotal, as survival rates exceed 90% when the disease is identified in its early stages. In response to this critical need, we introduce WFC2DS (Web Framework for Cervical Cancer Detection System), a novel expert web system specifically designed to revolutionize cervical cancer diagnosis. WFC2DS integrates a sophisticated ensemble of machine learning classification algorithms, including Artificial Neural Network (ANN), AdaBoost, K-Nearest Neighbor (KNN), Random Forest Classifier (RFC), Support Vector Machine (SVM), and Decision Tree (DT). This ensemble approach enables a comprehensive analysis of a large dataset comprising information from 858 patients with 36 attributes, with the primary objective being the early detection of cervical cancer, using the last attribute, Biopsy, as the target variable. Our evaluation criteria encompass accuracy, specificity, sensitivity, and the F1 score. Among the algorithms, RFC and DT emerge as the most promising, demonstrating exceptional performance with an accuracy of 98.1% and an F1 score of 0.98. AdaBoost shows an accuracy of 97.4% and an F1 score of 0.98, ANN attains an accuracy of 97.7% F1 score of 0.96, SVM achieves an accuracy of 96.2% and an F1 score of 0.96, and KNN reaches an accuracy of 90.6% with an F1 score of 0.91. This research significantly contributes to reducing the global burden of cervical cancer, emphasizing transformative advancements in women's healthcare. WFC2DS, with its cutting-edge machine learning techniques, not only improves the accuracy of cervical cancer diagnosis but also enhances the overall healthcare landscape for women worldwide.

INDEX TERMS Expert web framework, cervical cancer detection, gyne cancer diagnosis, Biopsy, Internet of Things, machine learning.

I. INTRODUCTION

Authors Cervical cancer poses a significant global threat to women's health, ranking as the fourth most dangerous type after breast, lung, and colorectal cancer. A critical characteristic of this malignancy is the absence of symptoms during its early stages. The development of cervical cancer occurs gradually over years and decades as premalignant cells progress to malignant tissues within the cervix [1]. Early detection and timely treatment of cervical cancer are

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pivotal in ensuring patient survival, with over 90% chances of successful outcomes and reduced treatment costs. Vaccination against human papillomavirus (HPV) is an effective preventive measure against this disease.

The incidence of cervical cancer is highest in emerging states and ranks third in advanced countries. In China alone, approximately 140,000 new cases of cervical cancer are diagnosed each year, accounting for 28% of all global cases. Cervical cancer ranks first among reproductive span malignancies in China [2]. Sub-Saharan Africa faces a substantial burden, with an alarming diagnosis rate of 34.8 cases per 100,000 women and a mortality rate of 22.5 cases per 100,000 women [3].

Currently, the Thinprep Cytology Test (TCT) and HPV diagnosis are the most effective procedures for cervical screening. The HPV test detects the presence of any viruses that may lead to cervical lesions or cancer. At the same time, TCT identifies abnormal changes in cervical cells, a significant precursor to cervical cancer [4]. Smoking has been identified as a prominent risk factor for cervical infection, with studies indicating that women who smoke are three times more likely to develop cervical cancer [5].

HPV, the virus responsible for cervical cancer, is primarily transmitted through sexual contact. Consequently, the risk of cervical cancer is strongly associated with factors such as the number of childbirths, sexual relationships, age of first sexual encounter, and contraceptive use [6]. Diagnostic methods such as the Pap smear (also known as the Pap test) and visual check using acetic acid (VIA) are utilized to detect cervical cancer. The Pap smear collects tissue samples from the vagina and cervix surface for microscopic examination of abnormal cell changes. VIA involves applying 3% to 5% acetic acid to the cervical lesion, which turns white if an infection occurs. Late-stage detection of cervical cancer can involve the use of magnetic resonance imaging (MRI) [7] and diffusion-weighted imaging (DWI) [8].

Previous studies have demonstrated substantial variations in HPV infection probabilities across different age groups. Early detection is crucial for effective prevention of cervical cancer. However, the rapid spread of this disease is attributed to factors such as insufficient awareness among women, low educational levels, and the presence of risk factors that hinder access to timely treatment. Cervical cancer incidence rates are significantly lower in developed countries compared to less developed ones, suggesting that effective control of these factors can significantly reduce cervical cancer cases.

Deaths resulting from cervical cancer can be significantly prevented by ensuring the availability of accessible screening facilities for women. However, many women are reluctant to undergo the biopsy test, which is critical in diagnosing cervical cancer. In light of this challenge, our study emphasizes the importance of Biopsy in diagnosing cervical cancer. By highlighting the significance of Biopsy, we hope to encourage women to undergo the diagnostic phase, ultimately saving more lives.

To achieve this objective, our study employs a multi-algorithm approach in developing a model for categorizing cervical cancer. By utilizing machine learning algorithms such as SVM, KNN, RFC, DT, ANN, and Adaboost, we aim to enhance the accuracy of cervical cancer detection. Our proposed method holds great promise in assisting gynecologists in accurately diagnosing cervical cancer among patients.

The contributions of this paper are as follows:

1. Developing an Expert Web System: The primary objective is to create and introduce the WFC2DS (Web Framework for Cervical Cancer Detection System), which serves as an expert web system designed to revolutionize cervical cancer diagnosis. This system aims to provide an innovative and accessible platform for early detection and diagnosis of cervical cancer.

2. Comprehensive Data Analysis: Conduct a thorough and comprehensive analysis of a large dataset comprising information from 858 patients with 36 attributes. The objective is to leverage advanced machine learning classification algorithms to identify the most effective model for early cervical cancer detection. The study focuses on metrics such as accuracy, specificity, sensitivity, and F1 score to evaluate model performance.

3. Improving Early Detection: The overarching goal is to contribute to the enhancement of early cervical cancer detection. By selecting and fine-tuning the most promising machine learning algorithm (RFC and DT) and demonstrating its remarkable accuracy, the study aims to pave the way for improved healthcare outcomes for women worldwide.

Through these contributions, we hope to impact the early detection and prevention of cervical cancer, ultimately reducing the mortality rate associated with this disease.

The subsequent sections of the paper are organized as follows: the second section provides a review of similar works, followed by the methodology, results, and conclusion of our proposed work. Each section offers a detailed exploration of specific aspects, providing a comprehensive understanding of our research and its organization.

II. RELATED WORK

Several researchers have made notable contributions to cervical cancer detection, aiming to prevent the progression of this disease, especially in developing countries. This section presents a summary of related work conducted in cervical cancer detection.

The Pap smear test is a widely used early-stage cervical cancer diagnosis technique. Singh and Goyal [9] explored various methods for detecting cervical cancer using a dataset derived from Pap smears. The research focused on segmentation techniques, with different algorithms demonstrating varying levels of accuracy, recall, precision, and F1 score. However, the main concern with this approach was the time cost associated with achieving higher accuracy levels.

Deng et al. [10] proposed a multi-algorithm approach for cervical cancer detection, utilizing Support Vector Machine (SVM), XG Boost, and Random Forest Classifier (RFC) to categorize cervical cancer based on four target variables. The comparison of these algorithms showed that XG Boost and RFC consistently yielded more reliable results compared to SVM.

Kudva et al. [11] developed a machine learning model for cervical cancer detection using a shallow Convolutional Neural Network (CNN) algorithm. This approach utilized cervix images obtained from 102 women after applying 3%-5% acetic acid. The algorithm demonstrated efficient results, achieving 100% accuracy in cervical cancer detection. Unlersen et al. [12] implemented a technique for categorizing cervical cancer using k-Nearest Neighbors (k-NN), Multilayer Perceptron, and Bayes Net classification algorithms.

In [13], the authors discussed the challenges in preventing cervical cancer in low- and middle-income countries (LMICs). The authors reviewed the current standards of care, biomarkers, and emerging technologies for cervical cancer detection, focusing on their adaptability to LMICs. They emphasized the need for affordable, simplified tests, improved imaging approaches, and the potential for decision support to enhance performance. In [14], the authors proposed a new approach that uses a multiscale fuzzy clustering algorithm to segment cervical cell images at different scales. They also introduced a new concept called ''interesting degree'' based on the area before assessing a node's significance. This helps to resolve the issue of selecting categories in clustering. Song et al. [15] presented a model for individual cell segmentation in cervical cancer detection using a dataset of pap smear images. The proposed method employed discrete labeling with appropriate functions for cell separation, with an evaluation demonstrating improved efficiency compared to previous approaches.

Ashok and Aruna [16] proposed an attribute selection-based model using an SVM classifier for cervical cancer detection. Image segmentation was performed using aviation, and features were selected using sequential progressive search, shared knowledge, random feature selection, and sequential floating forward search. The sequential floating forward selection approach outperformed other methods, achieving 98.5% accuracy, 98% sensitivity, and 97.5% specificity.

In another study, the K-Nearest Neighbors (KNN) technique was applied by the author [17] to a dataset of Thinprep Cytology Test (TCT) images for categorizing cervical cancer stages. The classification accuracy achieved was 82.9%. Kumar et al. [18] proposed an automated model for diagnosing and categorizing cervical cancer using images obtained from biopsy tests. The model utilized K-means clustering and K-nearest neighbor algorithms for image segmentation and achieved a performance accuracy of 92%.

Song et al. [19] introduced the multiscale convolutional network (MSCN) method for dissecting the cytoplasm and nuclei of the cervix. The method utilized deep learning techniques and demonstrated promising results for targeted region segmentation. Chankong et al. [20] employed the fuzzy C-means method to classify automatically and segment cervical cancer cells. By incorporating artificial neural networks (ANN) for authentication, the approach achieved 93.78% accuracy with seven classes and 99.27% accuracy with two classes. Song et al. [21] applied CNN-based segmentation methods for cervical cancer cell nuclei detection, obtaining 94.50% accuracy.

Lu et al. [22] employed a segmentation approach for the nuclei and cytoplasm of intersecting cervical cells. The author utilized various level-set methods to overcome challenges distinguishing cells with significant overlap. Unsupervised classification, nuclei and cytoplasm segmentation, and cervical cell optimization were achieved through scene segmentation. In [23], authors developed a computer-assisted screening system that uses digital image processing to analyze Pap smear images. The system works by segmenting the cells in the image, extracting features from the cells, and finally classifying the cells as normal or abnormal using a bagging ensemble classifier.

In [24], this study introduces a new method for cervical cancer detection called Neutrosophic Graph Cut-based Segmentation (NGCS). NGCS works by first preprocessing the cervical images to improve the quality of the images. Then, it transforms the images into Neutrosophic sets, which are a type of sets that can have three values: true, false, and unknown. This helps to address the problem of overlapping contexts in the images. Next, NGCS applies an indeterminacy filter to the images to reduce the amount of uncertainty. This helps to improve the accuracy of the segmentation. Finally, a weighted graph is constructed, and a maximum flow graph approach is used to achieve optimal segmentation. The study found that NGCS-based cervical cancer detection yields consistently superior results than traditional graph cut-oriented approaches. It outperformed these approaches by an average of 13%.

In [25], machine learning techniques like neural networks, SVM, random forest, and XGBoost were analyzed to detect cervical cancer early using a UCI dataset. The models achieved high accuracy, showing machine learning's potential for improving cervical cancer prognosis and treatment. This study [26] developed a decision tree classification model to predict cervical cancer risk using patient medical records. Feature selection techniques like RFE and LASSO were used to determine the most predictive attributes. The model also employed sampling methods to address class imbalance in the dataset. With feature selection and sampling, the decision tree model achieved high accuracy, sensitivity and specificity in detecting cervical cancer cases.

III. SYSTEM MODEL

The algorithm presented is designed for diagnosing cervical cancer using a Multiple Classifier in WFC2DS. It begins by importing the necessary libraries and suppressing warning messages to ensure smooth execution. Next, it reads the cervical cancer dataset into a pandas DataFrame and sets the display options to make the data more readable. Additional libraries and modules are imported to support various tasks, such as data splitting, evaluation, and oversampling.

The algorithm then proceeds to split the dataset into features (X) and the target variable (y) and applies the ADASYN (Adaptive Synthetic Sampling) technique to balance the data, which is crucial for addressing class imbalance issues common in medical datasets. The resampled data is further divided into training and testing sets. An classifier is initialized and trained on the training data, making it capable of learning patterns and relationships within the dataset.

Once the classifier is trained, it is used to predict the target variable for the test data. Accuracy measures are calculated to assess the model's performance in terms of training and testing accuracies. A classification report is generated to provide detailed information about the model's precision, recall, and F1-score for each class. Additionally, a confusion matrix is computed to visualize the classifier's performance in distinguishing between true positives, true negatives, false positives, and false negatives.

To enhance the visual understanding of the confusion matrix, a heatmap is created. This heatmap visually represents the confusion matrix using color-coding, making it easier to interpret the results. Overall, this algorithm is a systematic approach to training and evaluating an MLP classifier for cervical cancer diagnosis, addressing data imbalance concerns and providing comprehensive performance metrics for assessment.

A. DATASET DESCRIPTION

The dataset utilized for this research was obtained from Universitario Hospital de Caracas in Caracas, Venezuela, and is managed by the dataset archive at the University of California, Irvine. It comprises information collected from 858 individuals, encompassing demographics, behaviors, and medical details. Table 1 provides an overview of the dataset attributes, with the first column denoting attribute names, the second column indicating sexually transmitted diseases, and the last column specifying the data type.

Within the dataset, various attributes represent different values. For instance, the attribute "IUD" signifies the usage of an Intrauterine Device for pregnancy prevention, while "IUD (years)" indicates the duration of IUD usage. Additionally, sexually transmitted diseases are represented by the acronym "STD," including AIDS (Acquired Immunodeficiency Syndrome), HIV (Human Immunodeficiency Virus), and HPV (Human Papillomavirus). The "Dx" attribute signifies the diagnosis of various diseases, such as human papillomavirus, cancer diagnosis, and cervical intraepithelial neoplasia (CIN) diagnosis, which play crucial roles in the spread of cervical cancer.

The dataset consists of 858 patient records with 36 attributes. The final attribute, "Biopsy," serves as the target variable. The dataset, initially containing 36 columns, underwent a meticulous selection process. the final set of 31 columns was chosen based on their relevance to the study objectives, with the exclusion of columns featuring a high percentage of null values. The dataset was randomly divided into training and testing sets to facilitate dataset analysis, with 70% allocated for training and 30% for testing and validation. The trained model on the test dataset was used to assess the effectiveness of the proposed model by calculating success rates.

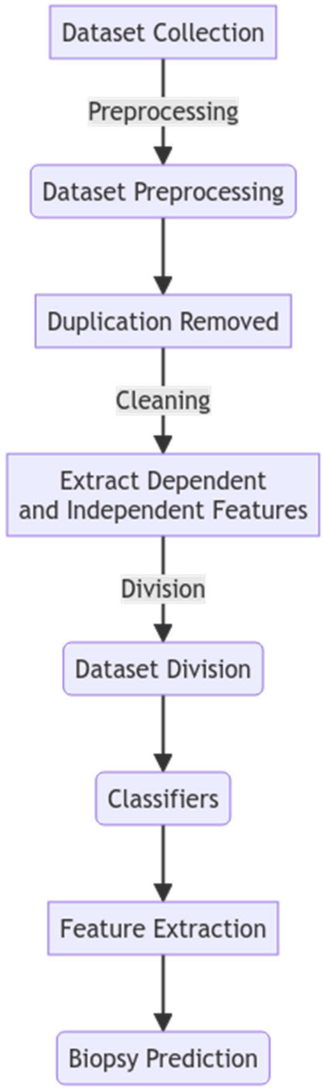

FIGURE 1. WFC2DS features extraction and decision system.

B. DATASET PREPROCESSING

During dataset preprocessing, specific steps were undertaken to ensure data quality and suitability for analysis. Notably, the attributes "Time since initial diagnosis" and "Time since the last diagnosis" for STDs contained over 80% null values and, as a result, were dropped from the dataset. Moreover, the attributes "Smokes" and "First sexual intercourse" contained several null values, which were subsequently removed from those respective columns. This process was performed manually, particularly for columns categorized as objects but

TABLE 1. Dataset attributes.

Sr.#	Attributes	Type
1.	Age	Integer
2.	Total no of sexual partners	
3.	Age of First sexual intercourse	
4.	Total no of pregnancies	
5.	Smoke(packs/year): No cigarette packs are used every year	
6.	Smoke (years): No of years women smoking	
7.	Hormonal Contraceptives (year)	
8.	IUD (Intrauterine device): (years)	
9.	STDs number	
10.	STDs: Time since the first diagnosis	
11.	STDs: Time since the last diagnosis	
12.	STDs: Number of diagnoses	
13.	Smokes	Boolean
14.	Hormonal Contraceptives	
15.	IUD	
16.	STDs (Sexually transmitted disease): syphilis	
17.	STDs:vulvo-perinealcondylomatosis	
18.	STDs:vaginalcondylomatosis	
19.	STDs:cervicalcondylomatosis	
20.	STDs:condylomatosis	
21.	STDs	
22.	STDs:molluscumcontagiosum	
23.	STDs: genital herpes	
24.	STDs: pelvic inflammatory disease	
25.	STDs: AIDS	
26.	STDs: HIV	
27.	STDs: Hepatitis B	
28.	STDs: HPV	
29.	Dx (Diagnosis): Cancer	
30.	Dx: CIN	
31.	Dx: HPV	
32.	Dx	
33.	Hinselmann	
34.	Schiller	
35.	Cytology	
36.	**Biopsy: Target Variable**	

required numerical representation, such as "Initial Sexual Encounter," "Based on number Sexual Partners," and "Number of total Births.

Data preprocessing techniques such as mean, distinct count, and approximate unique were applied to obtain dataset statistics. Table 2 provides a brief description of the dataset statistics, including precise approximate count (approximation of counting different elements), approximate unique count (count of unique elements), mean (average attribute value), minimum (occurrence count of the least frequent element), and maximum (occurrence count of the most frequent element). Null values were represented by zero in the statistics, and the corresponding columns were removed from the independent columns list, requiring imputation.

The independent columns were filled with mode or median values to handle null values, depending on their data type, except for the column designated for imputation. This approach involved machine learning-based imputation, where the column to be imputed was considered the 'Y' column. At the same time, the rest of the data served as the 'X' columns (excluding missing values for training the model). Consequently, only the 'Y' column contained null values that needed imputation. The test data comprised records with missing 'Y' values, while the training data contained complete 'Y' values. A machine learning model was trained using the filled values and employed to predict the missing 'Y' values.

Decision Tree Classifier models were created for categorical columns, while Decision Tree Regression models were employed for numerical columns.

C. K-NEAREST NEIGHBORS

K-Nearest Neighbors (KNN) is a versatile supervised machine learning algorithm that finds application in classification, regression, and clustering tasks. It determines the class membership or prediction of a data point by considering the labels or values of its k nearest neighbors in the feature space, making it particularly useful for both simple and complex problems. KNN's adaptability has led to its utilization in diverse domains such as computer vision, natural language processing, and bioinformatics [27]. While KNN's concept is intuitive, optimizing hyperparameters like "k" and selecting the most suitable distance metric, such as Euclidean or Manhattan distance, plays a crucial role in its performance, making it a valuable tool in a machine learning practitioner's toolkit.

$$y^\wedge = argmax\left(\sum\nolimits_{i=1}^{k} I\left(y_i = c\right)\right) \tag{1}$$

In the equation 1, y^ represents the predicted class label, and it is determined by selecting the class label c that occurs most frequently among the k nearest neighbors. The "argmax" function finds the class label c that maximizes this occurrence.

D. SUPPORT VECTOR MACHINE

The Support Vector Machine (SVM) algorithm, originally developed for two-class problems, was adapted to address the multi-classification challenge in this research. SVM uses a hyperplane to separate different classes in a dataset. By transforming the data into a higher-dimensional space, SVM seeks to maximize the margin between the classes, facilitating accurate classification [27], [28]. According to the previous study on STL, SVM is a parametric ML method. The SVM approach creates a correspondent hyperplane among the classes and data to split them [29]. A line represents a class separation structure in two-dimensional space but a flat line in three-dimensional space. SVM operates correspondingly to data points contiguous to the hyperplane in this process. If the distance between data points of classes increases, SVM gets more noise resistance [28]. The suggested study employs an SVM classifier with a linear kernel, a maximum of 100 iterations, a random state, class weights of zero, a tolerance of 0.0001, and several features of 31.

$$F(x) = sign(w.x + b) \tag{2}$$

In equation 2, f(x) is the classification function, w is the weight vector, x is the feature vector of the input data point, b is the bias term, dot (.) represents the dot product between w and x. sign is the sign function, which outputs +1 for positive values and −1 for negative values, effectively determining the class label. The goal of SVM is to find the optimal values for w and b such that the decision boundary maximizes the margin between the two classes while minimizing classification errors. In cases where the classes are not linearly separable, SVM can use kernel tricks to transform the feature space into a higher-dimensional space, allowing for a non-linear decision boundary.

E. RANDOM FOREST CLASSIFIER

The Random Forest Classifier (RFC) technique was employed due to its effectiveness in dataset classification, particularly when handling features with distinctive attributes. RFC constructs multiple decision trees using bootstrap samples and utilizes an ensemble learning approach to make predictions. By aggregating the results from individual decision trees, RFC achieves higher accuracy and robustness. Two random sampling strategies are used in sampling. Each sample technique is carried out with its row and column sampling. Effective back methods are used in row sampling, and repeated samples may be found in the sampled data sets. After this procedure, divided data sampling is used to generate the decision tree. Pruning is unnecessary because the randomization of two samples ensures the operation will be random, negating the necessity for pruning. The random forest procedure yields no over-fitting as the decision tree's length increases [31]. As the size of the decision tree increases, the model receives more randomness. Rather than looking for the crucial aspect. The outcome follows that the model has a wide range, which makes it better. It assigns a score to each important attribute rather than striving for the highest thresholds and changes the information so that the primary value of the results is 1. With a maximum depth of 2, a random state of 0, and 31 features, RFC uses 100 estimators in this study.

F. ADABOOST CLASSIFIER

The AdaBoost Classifier (ABC) was used as a meta-learner to combine weak classifiers. ABC iteratively trains a series of

TABLE 2. Statistical analysis of dataset attributes.

Attribute Name	Approximate Distinct count	Approximate Unique	Mean	Minimum	Maximum	Zeros	Zeros %
No. of sexual Partner	12	1.4%	2.542	1	28	0	0.0%
1st Sexual Intercourse	21	2.4%	16.995	10	32	0	0.0%
No. of Pregnancies	11	1.3%	2.2576	0	11	16	1.9%
Smokes(years)	30	3.5%	1.2164	0	37	722	84.2%
Smokes (packs/years)	62	7.2%	0.4463	0	37	735	85.7%
Hormonal Contraceptives (years)	40	4.7%	2.2241	0	30	269	31.4%
IUD (years)	26	3.0%	0.581	0	19	658	76.7%
Age	44	5.1%	26.8205	13	84	0	0.0%
Smokes	2	0.2%	-	-	-	0	0.0%
Hormonal Contraceptive	2	0.2%	-	-	-	0	0.0%
IUD	2	0.2%	-	-	-	0	0.0%
STDs	2	0.2%	-	-	-	0	0.0%
STDs (Number)	5	0.6%	-	-	-	0	0.0%
STDs (Condylomatosis)	2	0.2%	-	-	-	0	0.0%
STDs (CervicalCondylomatosis)	1	0.1%	-	-	-	0	0.0%
STDs (Vaginal Condylomatosis)	2	0.2%	-	-	-	0	0.0%
STDs (Vulvo-perineal Condylomatosis)	2	0.2%	-	-	-	0	0.0%
STDs(syphilis)	2	0.2%	-	-	-	0	0.0%
STDs (Pelvic Inflammatory)	2	0.2%	-	-	-	0	0.0%
STDs (Genital Herpes)	2	0.2%	-	-	-	0	0.0%
STDs (Molluscum contagiosm)	2	0.2%	-	-	-	0	0.0%
STDs (AIDS)	1	0.1%	-	-	-	0	0.0%
STDs (HIV)	2	0.2%	-	-	-	0	0.0%
STDs (Hepatitis B)	2	0.2%	-	-	-	0	0.0%
STDs (HPV)	2	0.2%	-	-	-	0	0.0%

TABLE 2. ***(Continued.)*** **Statistical analysis of dataset attributes.**

STDs (Number of Diagnoses)	4	0.5%	-	-	-	0	0.0%
Dx (Cancer)	2	0.2%	-	-	-	0	0.0%
Dx (CIN)	2	0.2%	-	-	-	0	0.0%
Dx (HPV)	2	0.2%	-	-	-	0	0.0%
Dx	2	0.2%	-	-	-	0	0.0%
Biopsy	2	0.2%	-	-	-	0	0.0%

weak classifiers on different training data distributions. ABC focuses on difficult samples by adapting the weights assigned to misclassified instances, enhancing the overall classification accuracy. AdaBoost has the best forecasting outcome compared to capturing, has reduced the error rate [32], and uses DT bases. At first, the weights of each sample in the data set were equal. Let x indicate the sample size for the data collection and y the objective. The target is displayed by the binary class, which is denoted by 0 and 1. A subset of the records in the data collection will be used to produce predictions of the initial decision-making tree stump. The sample weights will be modified after the initial prediction. The samples of data that were incorrectly categorized will be given more weight. The second iteration will select the examples with the maximum weights. The procedure will be repeated until the error rate fully decreases or reaches the target level.

G. ARTIFICIAL NEURAL NETWORK

ANN is a linked group of nodes that functions similarly to a brain's massive network of neurons. It is for binary classifiers that, during supervised learning, may identify how much an input relates to a specific class [33]. ANN is utilized to generate accurate results. The three main levels comprise the ANN architecture: the input, output, and hidden layers. Each layer is connected to the neurons by the number of images sent to the system. The number of input pictures used determines the number of nodes or levels in an ANN. Based on the input layer's data set, it processes and relates to the hidden layers. Using supervised and unsupervised learning techniques, two types of data sets accuracy. Multiple types of neural network algorithms, such as feed-forward and backpropagation, use the data set in several ways.

Combination and step forward are the two main steps of AdaBoost's sequential iterative technique. In the first iteration, all the occurrences in the training set have the same weight. The weights are modified in successive iterations based on error statistics. The weights of the occurrences with errors have been raised. The following equation 3 represents the binary class classification problem using training samples:

$$\{(a_i, b_i)\}_{i=1}^{T}, \quad b \in \{0, 1\} \tag{3}$$

P stands for the weak classifier linear combination. Equation 4 shows the result of combining the classifier.

$$P(x) = \sum\nolimits_{n=1}^{N} p_n c_n(x) \tag{4}$$

N is the total number of classifier, P is the weights, N is the number of weak classifiers, and P is the total number of weak classifiers. The classifier is trained after each iteration depending on the results of the preceding iteration, as shown in Equation 5.

$$P(x)_t = \mathrm{P}(x)_{t-1} + p_n c_n(x) \tag{5}$$

Pxt represents the classifier in iteration X_t. The Classifier performance at iteration t-1 is $\mathrm{P}(x)_{t-1}$.

Weights can be calculated by using this equation 6:

$$p_n = \frac{1}{2}\ln\left(\frac{i-o}{o}\right) \tag{6}$$

where the error rate of the weak classifier is represented by o.

H. DECISION TREE

Decision trees are one of the most prominent predictive modeling approaches in several fields, such as statistics, data mining, and machine learning. Decision tree sub-classes learning and property testing have recently received much attention. A decision tree computes a Boolean function in the manner described below: Given an input, the leaf's output is the value of the process on p. It can be reached by following a path that begins at the root and swings left or right at each internal node, depending on whether the variable's value in p is 0 or 1. The number of leaves influences the size of a tree. In a decision tree, the depth of a node determines the level's exit between the leaf node to the root. For all the values for the depth of its leaves, the depth of the tree is the greatest.

I. WFC2DS ARCHITECTURE

We have proposed real-time expert system architecture for Gynecologists to diagnose cervical cancer symptoms with

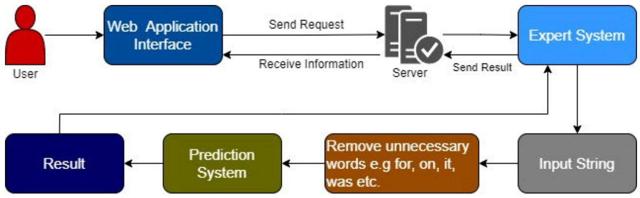

FIGURE 2. WFC2DS system architecture.

innovative machine learning techniques, as shown in Fig. 2. This system is a cloud system with numerous user accesses that allow many individuals to connect simultaneously. There is one global receiver that is common to all users. Web system with cloud computing was designed to detect cervical cancer. The cloud is the best option for a medical system that allows doctors to access data more effectively because it is a distributed network. The four phases of our suggested system are Data gathering, text data categorization, prognosis, and user interaction.

In a web application, the user and server communicate directly. A request is submitted to the server whenever someone interacts with the graphical interface. After considering the user's needs, the server decides where to send the demand. Therefore, the server seeks an intelligent system that may respond to the query and provide the desired results. After identifying the most effective expert system, the server allocates the users' duties. The intelligent system accepts user input as a string because the entire model is based on text, which is utilized in the early detection of cervical cancer. After eliminating extraneous words, the algorithm makes predictions. After eliminating unnecessary words, the prediction engine uses user-provided data to make predictions. The expert system gathers the results and sends them to the server. The user can check his results and proceed after the server sends them to the web interface.

J. DATA PRIVACY AND SECURITY IN WFC^{2}DS

Ensuring data privacy and security are paramount when handling sensitive medical information within the WFC2DS framework. The framework takes several measures to address these concerns and maintain patient data confidentiality while complying with relevant regulations such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States and the General Data Protection Regulation (GDPR) in the European Union:

-Encryption: The WFC2DS system employs encryption techniques to safeguard data both during transmission and storage. This prevents unauthorized access to patient information, ensuring that even if data is intercepted, it remains unreadable without the appropriate decryption keys.

-Access Control and Authentication: Access to the system is strictly controlled through authentication mechanisms. Only authorized individuals, such as medical professionals and patients, are granted access to specific sections of the system. User roles and permissions are defined to limit access to sensitive data.

-Anonymization and De-identification: The framework ensures that personally identifiable information (PII) is anonymized or de-identified before storage and analysis. This prevents the association of specific patient data with their identity, further protecting confidentiality.

-Audit Trails: Audit trails are maintained to track user interactions with the system. This ensures accountability and provides a record of who accessed the data and performed what actions.

-Secure Infrastructure: The WFC2DS framework is built on a secure and compliant infrastructure, utilizing industry best practices for data security. This includes firewalls, intrusion detection systems, and regular security updates.

-Data Minimization: The framework only collects and retains the minimum necessary patient data required for accurate diagnosis. Unnecessary data points are not collected, reducing the potential risk associated with data breaches.

-Consent Management: The framework includes mechanisms for obtaining patient consent to use their data for diagnosis and research purposes. Patients are informed about how their data will be used and can provide informed consent.

-Data Transfer Safeguards: When patient data is transferred between different components of the framework or to external systems, secure protocol HTTPS are used to ensure data integrity and prevent unauthorized interception.

By implementing these measures, the WFC2DS framework demonstrates a commitment to safeguarding patient data privacy and adhering to relevant regulations. These practices help build trust among users, patients, and regulatory authorities, ensuring that the system's benefits can be realized without compromising data security.

IV. RESULTS AND DISCUSSION

The dataset used in our proposed model was collected from the University Hospital de Caracas in Caracas, Venezuela. It consists of 858 images with 36 attributes. However, two attributes were excluded due to null values, and three represent cervical cancer tests. Therefore, only 31 attributes were used for training the cervical cancer classification model, with the target variable being the biopsy results.

Multiple criteria were considered to evaluate the efficiency of the machine learning classification model. Accuracy was the primary criterion, representing the percentage of correctly classified samples out of the total samples. Sensitivity and specificity were used to measure the ratio of accurately categorized positive and negative samples. The F1 score, which considers precision and recall rates, assessed the classifier's overall performance for binary classification.

The validation of the WFC2DS system is crucial to establish its reliability, generalizability, and suitability for real-world clinical settings. In our study, we adopted several approaches to validate the system's performance. Cross-Validation: Cross-validation techniques, such as k-fold cross-validation, were used to assess the WFC2DS system's performance on the dataset. This involves partitioning the data into subsets for training and testing to evaluate the system's accuracy and consistency. Hyperparameter Tuning: Hyperparameters of machine learning algorithms were tuned to optimize the system's performance. This ensures that the models are fine-tuned for the specific task of cervical cancer detection. Comparative Analysis: The performance of the WFC2DS system, particularly the AdaBoost algorithm, was likely compared against other machine learning classifiers. This comparison helps identify the strengths and weaknesses of each algorithm in the context of cervical cancer diagnosis.

The biopsy diagnosis for cervical cancer is influenced by several factors, which are explained below, along with their corresponding attributes. Notably, the top five characteristics, such as "Initial Sexual Encounter," "Based on several Sexual Partners," and "Number of total Births," are consistently observed.

The analysis reveals that women who had their first sexual intercourse between the ages of 15 and 18 are more susceptible to cervical cancer, according to the biopsy test. The age group primarily affected by this disease ranges from 20 to 35. Individuals with multiple sexual partners also show a higher likelihood of being affected by cervical cancer, with the age range of 20-35 most affected. Additionally, more pregnancies increase the chances of testing positive in the Biopsy.

Age and smoking habits also have an impact on biopsy results. Individuals who smoked and had their first sexual intercourse at a younger age have a higher risk of testing positive in the Biopsy. The number of pregnancies and smoking also demonstrate a detrimental effect on biopsy results. Although non-smokers can also test positive in the Biopsy, the proportion of smokers affected by cervical cancer is higher than non-smokers. The use of birth control devices is another significant factor influencing biopsy results. Individuals using intrauterine devices (IUDs) for birth control are highly prone to testing positive in the Biopsy, particularly those who use IUDs for an extended period. Hormonal contraceptives are also used for birth control but are less effective than IUDs.

Sexually transmitted diseases (STDs) also play a role in biopsy results. Various conditions, including human papillomavirus and AIDS, are transmitted through sexual intercourse. While other diseases are transmitted through sexual intercourse, the prevalence of patients with STDs is relatively low, resulting in fewer chances of testing positive in the Biopsy. RFC can be applied not only for disease prediction but also as a ranking mechanism to identify the most relevant factors for classification.

A. COMPARISON OF ML APPROACHES

In the WFC2DS system for cervical cancer diagnosis, AdaBoost exhibited superior performance compared to other approaches such as RFC, SVM, KNN, DT and ANN in predicting the Biopsy diagnosis. This finding is discussed in Table 3 of the study. The utilized algorithms demonstrated high accuracy and sensitivity, and specificity values. Moreover, the f1-scores for these models exceeded 0.95, indicating their robustness in accurately predicting the diagnosis.

The DT algorithm demonstrates high precision for both class 0 (99%) and class 1 (97%). It excels in capturing actual instances of both classes with a recall of 98% for class 0 and 99% for class 1. This results in balanced F1-scores of 0.98 for both classes, indicating strong overall performance.

The ANN model achieves high precision for class 0 (99%) and slightly lower precision for class 1 (96%). It also exhibits balanced recall rates for both classes, with a recall of 96% for class 0 and 99% for class 1. The resulting F1-scores of 0.98 for both classes indicate a well-rounded performance.

The AC demonstrates high precision for both class 0 (98%) and class 1 (97%). It also maintains balanced recall rates, with a recall of 98% for class 0 and 97% for class 1. The F1-scores of 0.98 for class 0 and 0.97 for class 1 indicate a good trade-off between precision and recall.

Similar to the Decision Tree, the RFC achieves high precision for both class 0 (99%) and class 1 (97%). It captures a significant proportion of actual instances for both classes, resulting in balanced F1-scores of 0.98 for both classes.

The SVM model achieves slightly lower precision for both classes (97% for class 0 and 95% for class 1). However, it maintains a balanced trade-off between precision and recall, resulting in F1-scores of 0.96 for both classes.

The KNN algorithm exhibits relatively high precision for class 0 (96%) but lower precision for class 1 (86%). It has a lower recall for class 0 (85%) and a higher recall for class 1 (97%). The F1-scores show a trade-off between precision and recall, with a score of 0.90 for class 0 and 0.91 for class 1.

1) DECISION TREE (DT) VS. K-NEAREST NEIGHBORS (KNN)

- DT achieves high precision for both class 0 (99%) and class 1 (97%), indicating a strong focus on accurate positive predictions.
- In contrast, KNN exhibits relatively high precision for class 0 (96%) but significantly lower precision for class 1 (86%).
- DT maintains a balanced recall rate for both classes (98% for class 0 and 99% for class 1), while KNN has a lower recall for class 0 (85%) but a higher recall for class 1 (97%).
- The F1-scores reflect this trade-off, with DT achieving balanced F1-scores of 0.98 for both classes, while KNN's F1-scores show a trade-off between precision and recall, with 0.90 for class 0 and 0.91 for class 1.

2) ENSEMBLE METHODS (ADABOOST AND RANDOM FOREST) VS. INDIVIDUAL MODELS (DECISION TREE AND K-NEAREST NEIGHBORS)

- Both AdaBoost and Random Forest (ensemble methods) demonstrate high precision for both class 0 (98% and 99%, respectively) and class 1 (97% for both), similar to the individual Decision Tree model.
- In contrast, the individual k-Nearest Neighbors (KNN) algorithm exhibits lower precision for class 1 (86%), indicating that ensemble methods might be more effective in maintaining precision.

TABLE 3. Performance analysis of embedded machine learning algorithms in the WFC2DS detection system.

Algorithm	Precision		Recall		F1-score	
	0	1	0	1	0	1
DT	0.99	0.97	0.98	0.99	0.98	0.98
ANN	0.99	0.96	0.96	0.99	0.98	0.98
AC	0.98	0.97	0.98	0.97	0.98	0.97
RFC	0.99	0.97	0.98	0.99	0.98	0.98
SVM	0.97	0.95	0.96	0.97	0.96	0.96
KNN	0.96	0.86	0.85	0.97	0.90	0.91

- Despite the high precision, ensemble methods such as AdaBoost and Random Forest still manage to maintain balanced recall rates, resulting in F1-scores of 0.98 for both classes. This suggests that ensemble methods can effectively balance precision and recall.

3) ARTIFICIAL NEURAL NETWORK (ANN) VS. SUPPORT VECTOR MACHINE (SVM)

- The Artificial Neural Network (ANN) and Support Vector Machine (SVM) both achieve high precision for class 0 (99% and 97%, respectively).
- However, ANN has a slightly lower precision for class 1 (96%) compared to SVM (95%).
- Despite the difference in precision, both ANN and SVM maintain a balanced trade-off between precision and recall, resulting in F1-scores of 0.98 for class 0 and 0.96 for class 1 in the case of SVM and F1-scores of 0.98 for both classes in the case of ANN.
- This comparison showcases that while both ANN and SVM maintain balance, ANN achieves slightly higher precision, indicating its strength in accurate positive predictions.

4) SVM VS. K-NEAREST NEIGHBORS (KNN)

- SVM exhibits higher precision for both classes compared to KNN (97% vs. 96% for class 0 and 95% vs. 86% for class 1).
- KNN, on the other hand, shows a higher recall rate for class 1 (97%) compared to SVM (95%).
- Despite these differences, both SVM and KNN achieve similar F1-scores (0.96 for both classes in the case of SVM and 0.90 for class 0 and 0.91 for class 1 in the case of KNN).
- This suggests that SVM may be more suitable when precision is of greater importance, while KNN excels in capturing actual instances of class 1.

In Figure 3, confusion matrix of the proposed model is shown. The confusion matrix is a 2×2 matrix that summarizes the performance of the model on a binary classification task. Here's a breakdown of the confusion matrix:

True Positives (TP):

This represents the number of instances correctly classified as Class 1 (positive) by classifier.

False Positives (FP):

This represents the number of instances incorrectly classified as Class 1 (positive) by classifier when they were actually Class 0 (negative).

False Negatives (FN):

This represents the number of instances incorrectly classified as Class 0 (negative) by classifier when they were actually Class 1 (positive).

True Negatives (TN):

This represents the number of instances correctly classified as Class 0 (negative) by classifier.

The confusion matrix for DT indicates that it correctly identified 148 instances as Class 1 (TP), incorrectly classified 4 instances from Class 0 as Class 1 (FP), missed 2 instances of Class 1 and classified them as Class 0 (FN), and correctly identified 157 instances as Class 0 (TN).

The confusion matrix for ANN indicates that it correctly identified 149 instances as Class 1 (TP), incorrectly classified 6 instances from Class 0 as Class 1 (FP), missed 1 instances of Class 1 and classified them as Class 0 (FN), and correctly identified 155 instances as Class 0 (TN).

The confusion matrix for AC indicates that it correctly identified 146 instances as Class 1 (TP), incorrectly classified 4 instances from Class 0 as Class 1 (FP), missed 4 instances of Class 1 and classified them as Class 0 (FN), and correctly identified 157 instances as Class 0 (TN).

The confusion matrix for RFC indicates that it correctly identified 148 instances as Class 1 (TP), incorrectly classified 4 instances from Class 0 as Class 1 (FP), missed 2 instances of Class 1 and classified them as Class 0 (FN), and correctly identified 157 instances as Class 0 (TN).

The confusion matrix for SVM indicates that it correctly identified 145 instances as Class 1 (TP), incorrectly classified 7 instances from Class 0 as Class 1 (FP), missed 5 instances of Class 1 and classified them as Class 0 (FN), and correctly identified 154 instances as Class 0 (TN).

The confusion matrix for KNN indicates that it correctly identified 145 instances as Class 1 (TP), incorrectly classified 24 instances from Class 0 as Class 1 (FP), missed 5 instances of Class 1 and classified them as Class 0 (FN), and correctly identified 137 instances as Class 0 (TN).

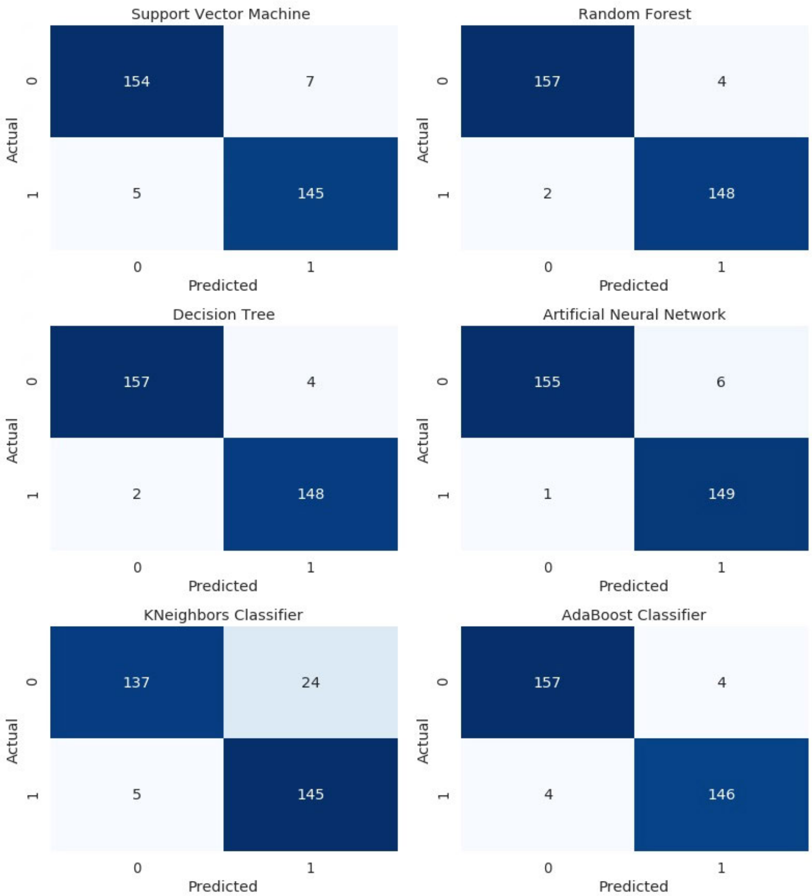

FIGURE 3. Confusion matrix of multiple classifiers used in WFC^{2}DS.

Table 4 presents a comparative analysis of various approaches for cervical cancer diagnosis, including the proposed WFC2DS method. The table references specific models employed in each approach and their corresponding accuracy scores. Notably, the WFC2DS approach outperforms all other methods, achieving the highest accuracy of 98%. This remarkable accuracy underscores its potential to significantly enhance cervical cancer diagnosis.

Approach [29], referred to as CervDetect, achieves an accuracy of 93%. In the case of the [30] Multilayer Perceptron approach, an accuracy of 93.33% is attained. Approach [31] employs a combination of three models—ExtraTreeClassifier, XGBoost, and Bagging—and attains an accuracy of 94.40%. Similarly, approach [32] utilizes Decision Tree, Random Forest, and XGBoost models, with an accuracy score of 93.33%. Approach [33] employs a Support Vector Machine with a Radial Bias Function and achieves an accuracy of 94.17%. Lastly, approach [34], [35] uses a Random Forest model and Bagging Decision Tree attains an accuracy of 91.80% and 91.2%.

Proposed WFC2DS presents the accuracy percentages achieved by different classification algorithms for cervical cancer diagnosis. These algorithms include K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree, Random Forest, Artificial Neural Network (ANN), and AdaBoost Classifier.

•**K-Nearest Neighbors (KNN)** achieved an accuracy of 90.6%.

•**Support Vector Machine (SVM)** achieved a higher accuracy of 96.2%.

•**Decision Tree and Random Forest** both achieved the highest accuracy of 98.1%.

•**Artificial Neural Network (ANN)** achieved a competitive accuracy of 97.7%.

•**AdaBoost Classifier** also performed well with an accuracy of 97.4%.

These results suggest that both Decision Tree and Random Forest algorithms, with their 98.1% accuracy, are the top-performing models among the proposed methods for cervical cancer diagnosis. Their high accuracy rates indicate their effectiveness in accurately classifying cervical cancer cases, making them strong candidates for clinical applications in this domain.

The superior performance of the WFC2DS approach is indicative of its potential to serve as a highly accurate diagnostic tool in cervical cancer detection. It is essential to note

TABLE 4. Performance comparison of WFC2DS with state-of-the-art approaches for cervical cancer.

References	Models	Accuracy (%)
[29]	CervDetect	93
[30]	Multilayer Perceptron	93.33
[31]	ExtraTreeClassifier, XGBoost, and Bagging	94.40
[32]	Decision Tree, Random Forest, and XGBoost	93.33
[33]	Support Vector Machine Radial Bias Function	94.17
[34]	Random Forest	91.80
[35]	Bagging Decision Tree	91.2
Proposed WFC^{2}DS	KNN	90.6
	Support Vector Machine	96.2
	Decision Tree	98.1
	Random Forest	98.1
	Artificial Neural Network	97.7
	AdaBoost Classifier	97.4

that methodological differences and innovative techniques employed in the WFC2DS approach may have contributed to its outstanding accuracy, emphasizing its significance in the field of cervical cancer diagnosis.

V. CONCLUSION

This study introduced the innovative WFC2DS framework for early cervical cancer diagnosis, employing various machine learning techniques, including SVM, RFC, KNN, AdaBoost, DT, and ANN. The dataset, sourced from UCI, comprised 858 records with 36 attributes. The target variable, Biopsy, which represents a cervical cancer diagnosis test, was analyzed independently in the experiments. Columns containing null or zero values were removed, resulting in the evaluation of models with 31 selected features. A critical aspect of this research was addressing the challenge of class imbalance in the dataset. To mitigate this issue and improve model performance, we applied the ADASYN data balancing technique. Among the proposed algorithms, RFC and DT emerged as the standout performer, achieving an impressive accuracy rate of 98.1%. This highlights the immense potential of the WFC2DS framework in significantly improving the accuracy of cervical cancer diagnosis, particularly when coupled with effective data balancing techniques. The WFC2DS framework is not limited to cervical cancer diagnosis alone; it holds promise for diagnosing various diseases and medical conditions.

Future research would broaden the data scope beyond UCI and carefully consider potentially significant features. Collaborating with medical professionals to conduct rigorous clinical validation is also critical. Exploring hyperparameter tuning beyond default settings and investigating alternative data balancing techniques, such as moving beyond ADASYN, would greatly benefit the study.

DATA AVAILABILITY STATEMENT

Dataset and code can be shared upon certain request to corresponding author.

A. CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest concerning the publication of this article.

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