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RESEARCH ARTICLE

Breaking Boundaries in Diagnosis: Non-Invasive Anemia Detection Empowered by AI

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ABSTRACT This article evolved because several instances of anemia are still discovered too late, especially in communities with limited medical resources and access to laboratory tests. Invasive diagnostic technologies and expensive expenses are additional impediments to early diagnosis. An effective, accurate, and non-invasive method is required to detect anemia. In this study, the conjunctival image of the eye is analyzed as a non-invasive method of detecting anemia. Various model approaches were tested in an endeavor to categorize anemic and healthy patients as accurately as possible. The Support Vector Machine (SVM) algorithm-integrated MobileNetV2 method was determined to be the most effective plan. With this combination, the accuracy of 93%, sensitivity of 91%, and specificity of 94%. These findings show that the model can successfully identify healthy patients while accurately identifying anemic patients. This method offers a non-invasive means of detecting anemia early on, making it promising for use in clinical settings. The SVM+MobileNetV2 technique relies on images of the eye's conjunctiva and can potentially improve healthcare by identifying people who may have had earlier anemia. This technique stands out as a solid option for the efficient and precise diagnosis of anemia when accuracy, sensitivity, and specificity are balanced.

INDEX TERMS Anemia detection, eye conjunctival images, MobileNetV2, non-invasive, SVM.

I. INTRODUCTION

A medical disease known as anemia occurs when the level of red blood cells in the bloodstream is below normal [1]. Red blood cells, also called erythrocytes, transfer oxygen from the lungs to various tissues and organs and carry carbon dioxide, a waste product, away from those tissues to be expelled through the lungs [2]. This helps the body function as a whole. According to epidemiological data, anemia, which affects over a third of the global population, is the most prevalent blood illness [3]. The detection process is also a complex challenge. WHO highlights that it is still difficult to accurately and thoroughly detect anemia everywhere globally, particularly in regions with developed economies.

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Anemia has a significant global impact, with considerable implications for social and economic growth [4]. Each government must examine the expenditures of combating the disease, which includes preventive, traditional analytical approaches, administration, and lodging services [5]. Estimating the financial and social consequences of anemic patients is very problematic. Some patients are frequently required to undergo recurrent laboratory tests, which might be inconvenient due to blood samples and raise transportation and/or support costs.

Anemia can be detected and diagnosed using a variety of procedures available to medical professionals [6]. These approaches aim to analyze the composition and quality of blood components, notably red blood cells, and their associated characteristics. One commonly used approach is a complete blood cell count (CBC), which provides a comprehensive overview of the different types of blood cells, including red blood cells, white blood cells, and platelets [6]. Another technique, known as a peripheral smear, involves the microscopic examination of a blood sample's cellular components, especially red blood cells [7]. This can reveal distinctive patterns or abnormalities in the cells' size, shape, and appearance, which can provide valuable insights into the presence of anemia and its underlying causes [8]. The reticulocyte count is another important diagnostic tool [9]. Reticulocytes are young, immature red blood cells released into the bloodstream from the bone marrow [10]. Serum iron indices, including parameters like serum iron, total iron-binding capacity (TIBC), and transferrin saturation, offer information about iron levels and utilization in the body [11]. Iron deficiency is a common cause of anemia, and assessing these indices can help identify whether anemia is related to insufficient iron availability [12].

Nonetheless, certain methods involve the uncomfortable process of drawing blood, which can induce fear or distress in some individuals. This underscores the importance of non-invasive alternatives [13]. Medical practitioners can gather valuable information about potential anemia cases by examining external signals in the body. In those with anemia, the pallor of the eyes, tongue, hands, and nails may be noticeable due to decreased oxygen levels. The pallor of the eyes, specifically, can provide significant indications of anemia. Therefore, the development of anemia diagnostic methods that are non-invasive, cost-effective, and easily accessible is paramount [13]. Notably, machine learning (ML) techniques have yielded successes across various fields, particularly in medicine, where they've been used to analyze anemia [14], [15], [16], [17], where ML methods that are widely used include K-Nearest Neighbor (KNN), Naïve Bayes (NB), Random Forest (RF), Support Vector Machine (SVM). KNN has the advantage of being easy to implement but is vulnerable to data changes and sensitive to outliers. Naïve Bayes stands out with its fast and straightforward performance, but its weakness lies in its naive feature independence assumption, which may not always hold. RF overcomes overfitting and is suitable for large datasets, but model complexity that is difficult to interpret and increased computing time can be an obstacle. SVM effectively handles model complexity, performs well in high-feature spaces, and efficiently deals with overfitting. Overall, SVM is a powerful and flexible method for classifying diverse datasets, even imbalances [18], [19], [20], [21]. SVM can also be applied as a deep learning (DL) model classifier layer. Even using SVM can improve the recognition performance of DL models [22], [23].

Convolutional neural network (CNN) is a DL method widely applied to image recognition or classification. The CNN model will affect performance, and knowledge is needed to design the CNN model. Pre-trained models are CNN models that have been taught various patterns and features from large datasets and can be used as a basis for performing various image recognition tasks. Advantages include efficient transfer learning, leveraging knowledge from large datasets, and overcoming data limitations. Many popular pre-trained models exist, such as VGG, DenseNet, Inception, ResNet, NasNet, Xception, MobileNet, etc [22], [23], [24], [25], [26], [27], [28]. MobileNetV2, a variant of MobileNet, is a model specifically designed for mobile applications with high computational efficiency and small model size. Its advantages involve customizable design, depthwise separable convolution for increased efficiency, and scaling multipliers for flexibility in adjusting model size according to application needs, in addition to being able to produce high accuracy [23], [25], [26], [29].

Research on automated non-invasive methods for anemia detection began several years ago; however, a comprehensive dataset for comparing these diverse approaches is currently lacking [13], [30]. A crucial aspect to note is that individual research groups often operated with their distinct datasets. In some instances, these datasets were notably small or lacked explicit details about the experimental setup. Furthermore, important considerations, such as the potential impact of ambient light during the image capture process, were occasionally overlooked or not thoroughly addressed. Additionally, the equipment used in some research is sophisticated and expensive, making it unsuitable for widespread industry development.

This research introduces a novel machine learning-based method that is non-invasive and cost-effective to facilitate the automatic identification of anemia, making a substantial contribution to addressing some of these unresolved difficulties. A training and testing process using conjunctival images from the Eyes defy-anemia simulation dataset collection was conducted on the hardware and software solutions given as well, with promising results. The methodology used in this work combines two strategies to solve the issue of imbalance in class data: the Synthetic Minority Over-sampling Technique (SMOTE) [31] and Tomek Links [32]. This study aims to develop a machine learning-based non-invasive, cost-effective automatic anemia detection system. One of the challenges in developing this method was the difference in the number of conjunctival images taken by anemic patients and healthy people. The SMOTE technique was used to construct synthetic samples from conjunctival images of anemic patients, increasing the number of samples in the minority class. Meanwhile, the Tomek Links technique deletes neighboring conjunctival image pairs between anemic and healthy patients. The conjunctival image data set got more balanced between the two classes by combining these two procedures.

Following the successful completion of the procedures to address the class imbalance, emphasis has shifted to implementing the three methods suggested in this work, namely SVM, MobileNetV2, and the MobileNetV2-SVM combination, in the anemia detection process. SVM is a data classification technique capable of recognizing complex patterns. Using balanced data, SVM could distinguish between healthy conjunctival images and those suggesting anemia.

MobileNetV2, on the other hand, is effective in object detection for various image modalities. In cases of anemia detection, MobileNetV2 can pay attention to visual features on conjunctival images that may indicate the existence of anemia. The MobileNetV2-SVM combination then makes use of these two approaches. The initial feature extractor, MobileNetV2, identifies essential aspects of the conjunctival images. The findings of the feature extraction are then presented to the SVM for final classification. As a result, the combination combines MobileNetV2's advantages in visual characteristic recognition with SVM's capacity to distinguish complicated patterns, yielding more robust and reliable anemia diagnosis findings. The rest of this paper is structured as follows. Section II contains literature concerning the diagnosis of anemia by non-invasive machine learning algorithm analysis, then Section III discusses the details of the research framework including data sources and recommended models for anemia detection. Section IV, experimentation and analysis of results, provides an in-depth explanation of how to run the experiment and the parameters used and is complete with information about the evaluation metrics used to measure model performance. Section V of the Conclusion of the analysis results section, in the final section, is a strong conclusion based on the analysis results and significant contributions.

II. RELATED WORKS

In recent years, the development of non-invasive methods to identify anemia has been the focus of many researchers. One of them is the use of machine learning algorithms, which have become increasingly popular to recognize and diagnose clinical disorders. For example, the work by Asare et al. used machine learning to detect iron deficiency anemia. Researchers tested algorithms such as Nave Bayes, CNN, SVM, k-NN, and decision trees to examine the color of the nails, the palpability of the palms, and the conjunctiva of the eyes to determine which method is more accurate at identifying anemia in children. The three stages of this work were dataset collection, data preparation, and model design for anemia diagnosis. According to the findings, SVM has the lowest accuracy, 95.4%, and CNN has the highest accuracy, 99.12%. These results demonstrate that anemia can be detected quite successfully using a non-invasive method [33]. Mannino et al. used a new, non-invasive method of diagnosing anemia in a different investigation. Using smartphone and artificial intelligence (AI) methods, they employed a remote procedure that enables quick screening to measure hemoglobin levels. This technique involves photographing the eye, automatically extracting the conjunctiva as a region of interest (ROI). The next step is to evaluate the ROI and extract key aspects to train machine learning algorithms to assess whether a person is anemic. This model has an accuracy of 85%, a precision of 86%, and a recall of 81% after being tested on more than 200 participants. These results suggest that a non-invasive strategy utilizing smartphone technology and AI can be useful for rapidly and reliably diagnosing anemia [34].

Through image analysis of the conjunctiva of patients from Italy and India, Dimauro's research has created a novel intelligent method based on machine learning that can automatically detect anemia. The scientific community can now access this data collection, which was produced through a series of meticulous tests. These systems stand out because they use inexpensive gadgets that are ideal for mass use and easier to get. Additionally, this study contrasts system performance with previously published methods. The machine learning algorithm used two distinct regions of the eye's mucous membrane in this study to diagnose anemia. In particular, the RUSBoost algorithm has demonstrated great performance in categorizing patients into those who have anemia and those who do not after being thoroughly trained using palpebral conjunctival images [13]. Even after accounting for the varying ethnic backgrounds of the study's patients, the results remained reliable. In a separate study, Dimauro put up a novel method for measuring anemia that consisted of three key contributions. They first applied a sclera segmentation algorithm on nearly obtained digital eye images to separate the sclera. Scientists then applied a vessel extraction method to locate the vessels in the images. Third, classifiers were employed to determine if a person was anemic or otherwise healthy. The study is based on the publicly available Eyes-Defy-Anemia dataset, which consists of 218 eye images obtained with a specific tool to minimize the impact of ambient light. Interesting results were obtained with good precision (88.53), recall (82.53), and F1 scores (84.10), particularly in the scleral segmentation test. The F2 score in the anemia identification job was 86.4% when utilizing the color feature of the entire sclera and 83.8% when using the vessel color feature alone [30]. Additionally, the color feature and the hemoglobin value appeared to correspond well. In a different investigation, Dimauro and Simone suggested a method they called graph partitioning segmentation. Semantic segmentation will be carried out with this method in regions with a specific diagnostic meaning. By using the normalized slice for perceptual division, this procedure tries to change the spectrophotometric characteristics of hemoglobin. Standard metrics and assessments of the connection between the color of the ROI and hemoglobin levels based on 94 samples are used to show the validity of this method. The age, sex, and hemoglobin content of these samples varied. The zones that are automatically segmented by this method are appropriate for diagnostic operations, particularly in calculating the quantitative amount of hemoglobin from the visible conjunctival tissue [35].

Similar to the previously discussed experimental findings, these findings center on the diagnosis of anemia via image analysis of the eye's conjunctiva. The researchers have also used a variety of techniques in the past, including classifiers built with machine learning algorithms, scleral segmentation, and color feature analysis. They looked for visual motifs that might represent anemia in patients. However, there are significant distinctions between this study and several earlier investigations. One of the contrasts is the strategy employed

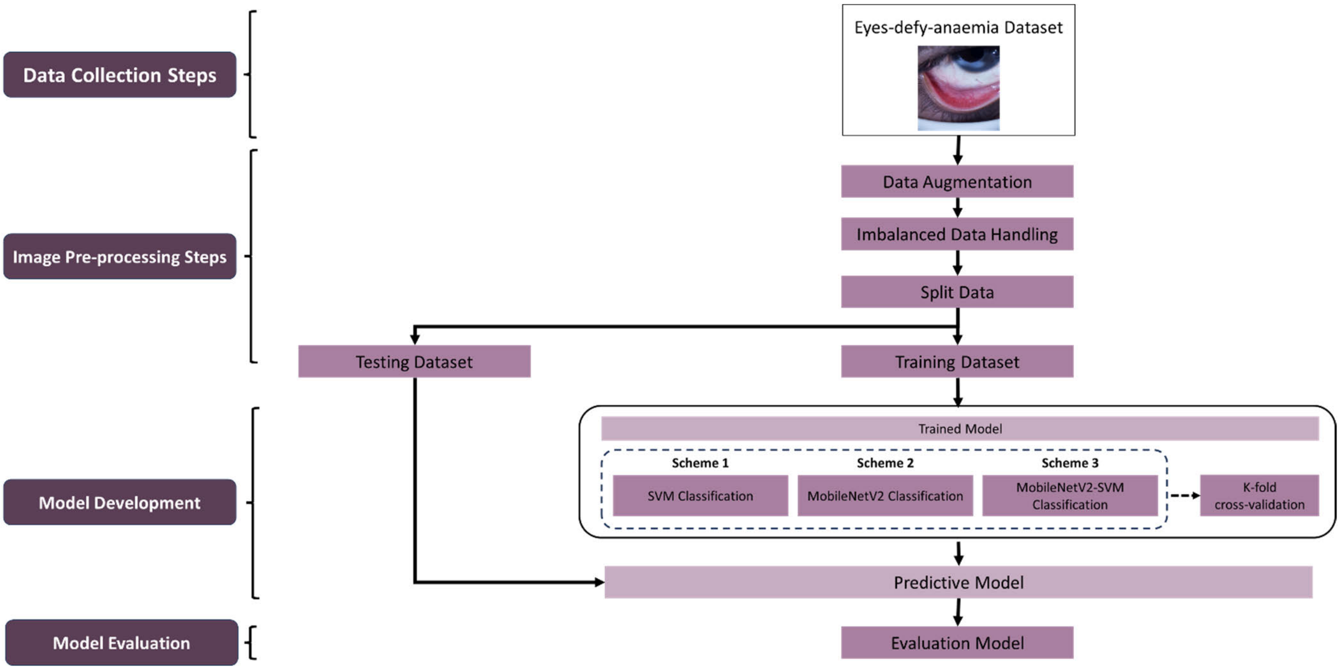

FIGURE 1. Pre-processed images obtained from the original image.

to address the class disparity. SMOTE and Tomek Links' combined strategy could produce superior outcomes in terms of accuracy and generalizability compared to previously used strategies. Additionally, this study focuses on the application of SVM, MobileNetV2, and the MobileNetV2-SVM combination in anemia detection. It recommends a combination of traditional methods and learning methods in tackling this issue. This research strategy may differ significantly from other approaches due to the data set employed and the usage of the MobileNetV2 algorithm, which has advantages in visual object recognition. This research has the potential to significantly contribute to the development of more precise and efficient anemia detection techniques by combining several algorithms and approaches to overcome class imbalances and utilizing cutting-edge technology.

III. MATERIALS AND METHODS

The research framework is divided into several parts (Figure 1), the first of which is data collection, with the "Eyes-defy-anemia" dataset serving as the data source. This dataset contains segmented images of patients' eyes from Italy and India. Subsequently, data preprocessing operations such as conjunctival image augmentation were performed to prepare the data for a machine learning application. Moreover, in this research framework, the SMOTE (Synthetic Minority Over-sampling Technique) and Tomek Links approaches are used to reconcile the differences in the number of samples between the classes of normal patients and anemic patients [36], [37]. After balancing the data, it is divided into two subsets: training and testing. To ensure that the classes are fairly represented in both subsets, the split employs the label stratification approach with a ratio of 70:30 [38], [39].

The preprocessed data is then prepared for the modeling stage, which comprises data normalization and feature extraction required for machine learning. This study framework employs three distinct modeling approaches: Support Vector Machine (SVM), MobileNetV2, and the MobileNetV2-SVM combination. Each methodology has its way of extracting and classifying information from images of the eye's conjunctiva. Following the modeling process, model evaluation is performed to assess the performance of each technique in detecting anemia. The success of these approaches was assessed using a variety of evaluation criteria. The evaluation results were utilized to conclude the effectiveness of the approaches in automatically detecting anemia through images of the conjunctiva of the eye in the final stage.

A. DATASET AND PRE-PROCESSING DATA

This study's dataset, Eyes-defy-anemia [13], is a significant contribution to efforts to identify anemia based on the pale conjunctiva of the eyes. This dataset contains eye images of Indian and Italian patients obtained with smartphones modified to fit devices. This shooting method exposes the majority of the eye area appropriately. The palpebral or total (palpebral and forniceal) conjunctival regions were then identified and separated manually from these eye images. This dataset consists of 211 image samples after removing certain samples based on specific criteria (Figure 2). It comprises segmented eye images with the same size (1067 × 800 pixels). Italian and Indian patients make up the two patient subgroups in this dataset. Blood samples from 123 Italian patients yielded

FIGURE 2. Example image of the data set used in this study.

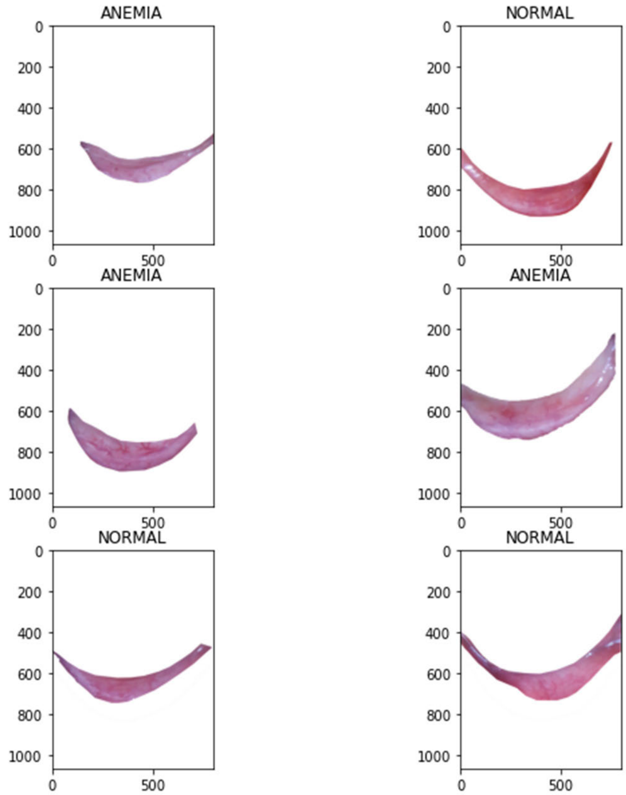

FIGURE 3. Pre-processed images were obtained from the original image.

images of their eyes. However, certain examples have to be left out of our investigation [13], [30]. Patients 1, 35, 54, 58, 75, and 109 were not included in the study because their forniceal conjunctiva, a particular eye area, was not apparent in images, while patient 93 was eliminated because of a drop in Hb concentration. 116 ocular images were thus utilized to analyze the Italian patient group. On the other side, there are 95 eye images and blood samples from Indian patients taken from Karapakkam, Chennai, India, and they are all marked as Indian data sets [13]. Each image contains segmented data such as palpebral conjunctiva, forniceal, and a combination. This allows us to correlate the level of pallor with hemoglobin (Hb) levels and assess the performance of the segmentation algorithm. The utilization of a dataset focusing on the forniceal conjunctiva is a significant difference in our investigation. A total of 211 eye image samples were collected and separated into two categories: 42 from anemic patients and the rest 169 from normal patients [13].

In addition to images and segmentation information, the collection includes additional critical information such as Hb values measured in the laboratory and the patient's age and gender. All of these elements contribute to more in-depth analyses and research that are more insightful and of high quality. This dataset can be used to design and test machine learning algorithms for detecting anemia based on conjunctival pallor and identify connections between clinical factors, including Hb value, age, and gender.

The data augmentation procedure on conjunctival images is included in the pre-processing step in this study. The purpose of augmentation is to enhance the variety of data used so that machine learning algorithms can learn from various situations [40], [41]. Several changes are applied to the conjunctival images in this context to build a richer and more diversified dataset. The resize process is one of the augmentation strategies used [42]. Initially, the conjunctival image comprises 800 × 1067 pixel dimensions and three colors components (R, G, and B). However, as part of the augmentation, the image is reduced to 224 × 224 pixels with three color components. This scaling reduces the image's size, making it more amenable to machine-learning algorithms analysis. Then, in each image, normalize the pixel values [43]. Each pixel value in the image is divided by 255.0, resulting in a pixel value ranging from 0 to 1. This ensures that the data used is evenly scaled and can be handled more readily by machine learning algorithms [44], [45]. Additionally, data augmentation is accomplished by duplicating images. The starting data is multiplied by three times the starting data. This procedure includes two forms of augmentation: rotation and flip [46]. The images will be rotated and mirrored (flipped) at an angle of -30 to 30 degrees. The label encoder method is used after the data augmentation step [47]. Each class label in the dataset will be converted to a numeric value to help with machine learning model training. Labels for this study are divided into two categories: "anemia" and "normal." To facilitate model processing, the label "anemia" will be represented by the number 0 and the label "normal" by the number 1. A label encoder turns the category class label into a numeric form that machine learning algorithms can understand [48]. This is called label encoder, and it involves converting categorical class labels into a numeric form that machine learning algorithms can read. Encoding labels guarantee that the model correctly understands and recognizes the target class during training [49], [50]. This step is critical before entering data into the machine learning model because it bridges the gap between class representations in text form and the numerical representations required by machine learning methods.

Figure 3 depicts the outcome of this preprocessing procedure, demonstrating the transformation of image data into a

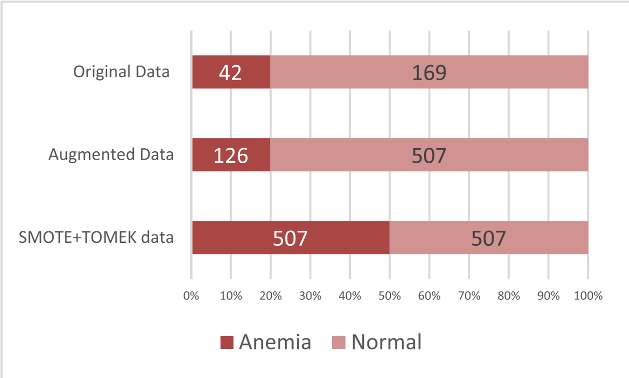

FIGURE 4. Composition of the dataset before and after handling the imbalanced data.

matrix format appropriate for analysis by machine learning. The purpose of this augmentation is to add more diversity to the dataset so that machine learning models can learn from varied image orientations and viewpoints [51] This augmentation is a typical method used in image data processing to improve the quality and variety of data utilized in machine learning procedures. Augmentation enriches the already used data set with different visual modifications so that machine learning algorithms can learn from various situations that may occur in the actual world [52]. This augmentation process transforms 42 anemic patients and 169 normal individuals into 126 anemic patients and 507 normal patients. This data, namely the imbalance data, will be processed further.

B. HANDLING IMBALANCED DATASETS

The next step is handling data imbalance. After it was discovered that there was still an imbalance in the augmented dataset, namely 126 patients suffering from anemia and 507 normal patients, the next step was to overcome this problem. SMOTE (Synthetic Minority Over-sampling Technique) and Tomek Links were used in this study to overcome class imbalance [36], [53]. SMOTE is an oversampling strategy that uses synthetic data based on existing samples to increase the number of samples in the minority class. This approach takes a random sample from the minority class, finds the nearest neighbor, then generates synthetic data by subtracting the sample from the nearest neighbor and multiplying it by a random number [37]. On the other hand, Tomek Links is an under-sampling strategy that seeks to lower the number of samples in the majority class. This approach finds sample pairs with different class labels that are the nearest neighbors to each other. In addition, the sample, the Tomek Links pair, is eliminated from the majority class [54].

This study combines both of these methods with the SMOTE + Tomek strategy, which entails using SMOTE to oversample the minority class and then using Tomek Links to remove samples from the majority class that are Tomek Links pairings. It attempts to balance the classes in the dataset by merging SMOTE and Tomek Links. This ensures that the machine learning model has a better probability of correctly understanding and recognizing both classes, resulting in more accurate anemia detection findings. The outcomes of the handling process for class imbalance are shown in Figure 4. With 507 for the anemic class and 507 for the normal class, it is clear from these results that the dataset's class composition has become balanced. A balanced distribution between the two classes was achieved through this treatment method, which may have improved the performance and precision of the machine learning model in identifying anemia. The model will more likely comprehend and predict the two classes effectively with a balanced composition. This is a crucial step to take to guarantee that the final model can accurately identify anemia in patients.

C. SPLIT DATASET PROCESS

The next stage is to split the data into training and testing subsets using the stratify label method with a ratio of 70:30 after completing the data pre-processing and handling the data imbalance [38], [39]. Preparing data for machine learning models is a crucial step. The Train-Test Split separates previously processed data into training data (train) and test data (test), two separate subsets. The ratio employed is 70:30, meaning that 70% of the data will be used to train the model, and the remaining 30% will be used to test the model's effectiveness. The stratified label approach divides the data into training and testing subsets. This indicates that the class distribution in the original dataset will be maintained in both subsets. This is necessary to guarantee that the test data accurately represents all classes [55].

D. PROPOSED ALGORITHM MODEL FOR CONJUNCTIVAL CLASSIFICATION

The modeling stage in this work consists of three independent proposed procedures, each with its own set of characteristics and methods for recognizing anemic individuals via the classification process. The three approaches are SVM, MobileNetV2, and the MobileNetV2-SVM combination. The flow of each scheme is presented in Figure 5. The method in this case refers to the strategy or algorithm used to extract and categorize features from eye conjunctival image data. The feature extraction method is critical because it retrieves and converts the important attributes of a image into a numerical form that machine learning algorithms can understand. In this case, SVM, MobileNetV2, and MobileNetV2-SVM combinations are among the approaches used. The following sections will detail how each of these methods is used in the context of modeling for anemia detection. This will provide you with a thorough grasp of the precise steps involved in each scheme and how they contribute to the detection of anemic patients.

1) CLASSIFICATION USING SVM ALGORITHM (SCHEME 1)

In Scheme 1 of this study, the SVM algorithm with a linear kernel was utilized to detect anemia in eye conjunctival image data [56]. The linear kernel SVM algorithm was chosen for

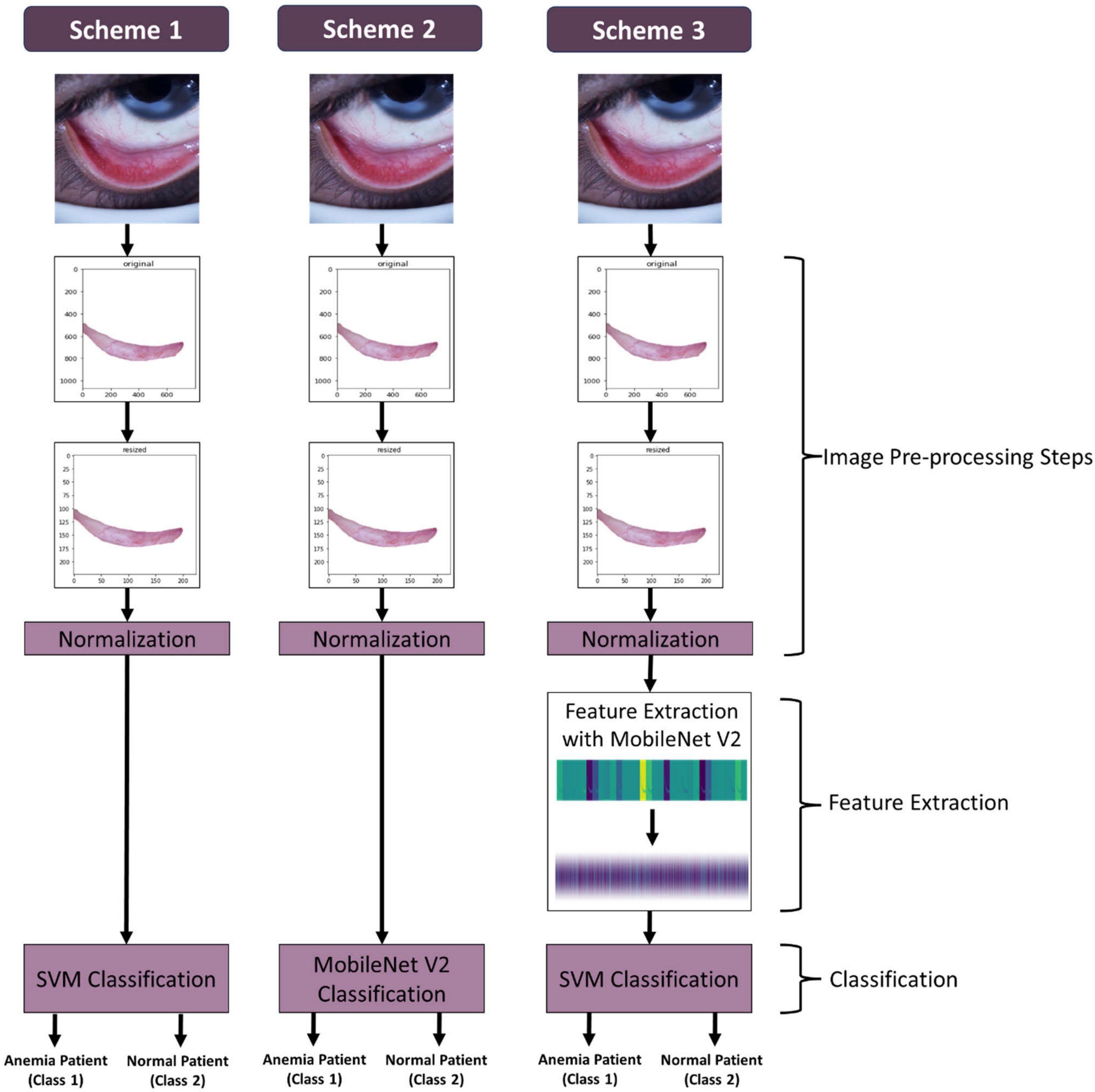

FIGURE 5. Algorithm flowchart for each scheme.

its ability to linearly separate two data classes, which is suitable when the separation pattern between the classes can be well characterized by a straight line in the relevant feature space [57]. The classification technique employs SVM and linear kernels to create a linear "line" or "hyperplane" that optimally separates the two data classes [58]. This line is positioned to have the greatest distance between it and points of different classes (referred to as support vectors) [59]. The core premise of SVM is retained. However, the SVM model aims to determine the best linear dividing line across distinct classes by employing a linear kernel [60], [61]. Dimension reduction is also conducted using PCA (Principal Component Analysis) techniques to assist in visualizing how SVM with a linear kernel distinguishes the two classes in a reduced feature space [62], [63]. PCA is used to condense feature dimensions into two core features that adequately explain data variation. The dimension reduction findings can be visualized in a two-dimensional plane, allowing us to comprehend how SVM with a linear kernel projects data into a smaller space [63].

2) CLASSIFICATION USING MobileNetV2 ALGORITHM (SCHEME 2)

The MobileNetV2 algorithm was used in Scheme 2 of this work to classify anemia detection in eye conjunctival image data. MobileNetV2 is a convolutional neural network (CNN) architecture intended primarily for image identification tasks [64], [65]. The advantage of MobileNetV2 is its effectiveness in extracting features utilizing lighter convolution processes, which makes it suited for usage in low-power devices such as mobile devices [66]. The MobileNetV2 classification approach begins with a feature extraction stage that employs a well-tuned CNN architecture [67]. MobileNetV2 will automatically analyze the important aspects of the conjunctival image data to discriminate between anemia indicators and normal images [68], [69]. The parameters of this network will be modified during the training phase so that the model can discover relevant patterns associated with different classes [68]. The MobileNetV2 algorithm in Scheme 2 is pre-configured and trained on large amounts of image data (often from the ImageNet dataset) for a common item recognition job. However, at this step, the model will be altered and retrained utilizing eye image datasets that have been pre-processed and imbalanced. The MobileNetV2 model can now recognize certain visual features linked with anemia on conjunctival images of the eye. Overall, Scheme 2 shows how the MobileNetV2 algorithm may be used as a classification tool to detect anemia in eye image datasets. This technique uses MobileNetV2's competence in pattern recognition and feature extraction, which has been tailored to the specific data in this investigation.

3) CLASSIFICATION USING SVM+MobileNetV2 ALGORITHM (SCHEME 3)

In this study, Scheme 3 used a combination of the SVM (Support Vector Machine) and the MobileNetV2 algorithms to perform classification for anemia detection in eye conjunctival image data. This combo intends to maximize anemia detection outcomes by leveraging the advantages of each method while dealing with classification challenges. The feature extraction stage of the SVM+MobileNetV2 combination classification procedure begins with the MobileNetV2 algorithm [70]. The MobileNetV2 model will analyze conjunctival images to find visual features related to anemic symptoms. The feature extraction findings are then sent into the SVM algorithm. SVM will use the characteristics gathered by MobileNetV2 to construct a classification model. The fundamental goal of SVM is to distinguish between normal and anemic conjunctival images by establishing an ideal "line" or "hyperplane" between the two classes [56]. This combination enables the use of MobileNetV2's capabilities for deep feature extraction from images as well as SVM's capabilities for building good class boundary separations [71]. This combination produces a more robust classification model capable of producing a more accurate prediction of anemia detection. Using Scheme 3, this work attempts to integrate the benefits of the SVM and MobileNetV2 algorithms in a single model capable of detecting symptoms of anemia on images of the eye's conjunctiva. Combining diverse methodologies has the potential to increase anemia diagnosis performance greatly.

All schemes are validated during the modeling process using the K-fold or K-fold cross-validation approach, as shown in Figure 1. This validation aims to evaluate the proposed model's performance in each scheme [72], [73]. The K validation-fold technique divides data into groups or "folds" with different k values for cross-validation [73]. For each iteration, one of the folds will be used as testing data, while the other k-1 folds will be used as training data. This procedure is repeated k times to ensure that each fold serves as both test and training data. K-fold validation must be done appropriately to decrease variations and produce consistent and reliable results. The primary purpose of K-fold validation is to offer a more stable estimate of model performance as well as reliable information regarding training errors. The K-fold validation strategy with $k = 5$ was utilized in this experiment [74], [75]. This means the data will be folded five times and the validation procedure will be performed five times. One of the folds is utilized as test data during each iteration, while the other four folds are used as training data. This helps evaluate the model fairly and consistently across different data subsets.

E. EVALUATION MODEL

The model evaluation stage, which occurs at the end of the modeling process, attempts to assess the model's performance in detecting anemia in the eye conjunctival image dataset [76]. Several critical criteria are used in this evaluation to understand better how the model acts when classifying data. Accuracy, sensitivity, and specificity are the measurements employed [77].

1) ACCURACY

Accuracy assesses the model's overall ability to predict correctly. In this investigation, accuracy will indicate how effectively the model classifies conjunctival images of the eyes as anemic or overall normal. This is critical for evaluating the model's overall performance [77].

2) SENSITIVITY (TRUE POSITIVE RATE)

Sensitivity assesses the model's ability to identify true positive cases. Sensitivity will reflect how effectively the model can recognize images of the conjunctiva of the eye that show symptoms of anemia in the setting of this investigation [19], [78]. Sensitivity is required to ensure that the model can identify patients who may have anemia.

3) SPECIFICITY (TRUE NEGATIVE RATE)

This metric assesses the model's ability to identify real negative cases [79]. In this situation, specificity indicates how well the model recognizes images of the conjunctiva of the eye that are genuinely normal. Specificity is required to ensure that the model does not incorrectly categorize healthy patients.

We can acquire a more complete image of model performance by using these indicators. Accuracy provides a basic image of how well a model can predict, whereas sensitivity and specificity assist us grasp a model's capacity to distinguish between positive and negative classifications independently. Based on the previously mentioned modeling scheme, the findings of this study will provide an understanding of the extent to which the suggested model is effective in recognizing and discriminating conjunctival images of the eye indicating signs of anemia from normal ones.

IV. RESULT AND DISCUSSIONS

A. EXPERIMENT RESULT

This study aims to create a conjunctival image-based anemia diagnosis system based on the three proposed model schemes. The experimental results of the three previously proposed model schemes will be discussed in this sub-chapter. The results of this experiment provide insight into the performance of each model in identifying images of the conjunctiva of the eye as anemic or normal. The experimental results from the three model schemes will provide insight into how well each model recognizes symptoms of anemia on images of the eye's conjunctiva. This will aid in determining the efficacy and applicability of each model approach for detecting anemia in pre-processed image data. As a result, this sub-chapter will provide a thorough summary of the experimental results as well as the performance of each model scheme in the context of conjunctival image-based anemia detection in the eye.

1) CONJUNCTIVAL IMAGE CLASSIFICATION USING THE SVM ALGORITHM (SCHEME 1)

This work applies the SVM approach with a linear kernel in the first classification. A linear kernel is an SVM function that handles data that is intended to be classified linearly. Each type of kernel in SVM has distinct qualities, and in the case of a linear kernel, extra parameters known as C or cost parameters must be modified. The linear kernel on SVM seeks to find the best-dividing line between data by optimizing parameter C. This parameter determines the trade-off between allowing for more misclassification of training data (to prevent overfitting) and minimizing misclassification of test data (to avoid underfitting).

Parameter C is optimized during the linear kernel procedure to attain the best classification accuracy. This entails testing numerous models with varying values of C or using a trial-and-error approach. The outcomes of parameter C optimization using a linear kernel can be evaluated using a classification performance measure, which is commonly tested using accuracy measures. This work seeks to determine the parameter C that provides the best classification accuracy in identifying anemia based on images of the eye's conjunctiva using a linear kernel in SVM. Based on the ideal selection of parameter C, the SVM model with a linear kernel can classify conjunctival images as anemic or normal as precisely as feasible.

TABLE 1. The results of adjusting parameter C's value in Scheme 1 on the testing dataset.

Fold	PARAMETER C	Accuracy	Sensitivity	Specificity
Fold 1	1	0,8732	0,7465	1,000
	10^{-1}	0,8732	0,7465	1,000
	10^{-2}	0,8662	0,7465	0,986
Fold 2	1*	0,8873	0,8451	0,930
	10^{-1}	0,8873	0,8451	0,930
	10^{-2}	0,8873	0,8451	0,930
Fold 3	1	0,8873	0,8028	0,972
	10^{-1}	0,8873	0,8028	0,972
	10^{-2}	0,8732	0,7746	0,972
Fold 4	1	0,8662	0,8028	0,930
	10^{-1}	0,8662	0,8028	0,930
	10^{-2}	0,8662	0,8028	0,930
Fold 5	1	0,8794	0,7714	0,986
	10^{-1}	0,8794	0,7714	0,986
	10^{-2}	0,8794	0,7714	0,986

*Optimal parameter C value in Scheme 1.

Table 1 displays the experimental results from the first classification using the SVM method with a linear kernel. At this stage, researchers examine various values of parameter C to improve classification performance on training and testing data. Parameter C was tested with three different values in this experiment: 10^{-2}, 10^{-1}, and 1. Model performance was evaluated using several parameters, including accuracy, sensitivity, and specificity. The trade-off between permitting the misclassification of training data and reducing the misclassification of test data is governed by parameter C. The experimental results indicate that the optimal parameter C is 1, with training data classification performance reaching 91.2% accuracy, 83.0% sensitivity, and 99.3% specificity. When the model with the best C parameter is tested on the test data, the best results are on the second cross-validation, it achieves an average accuracy of 88.73%. The sensitivity was 84.5%, while the specificity was 93%. This demonstrates that the SVM model with a linear kernel can detect anemia in conjunctival images, despite differences in performance across K-fold cross-validation iterations.

Figure 6 depicts the confusion matrix of the best model from Scheme 1. The algorithm correctly predicted that 151 conjunctival images depicted anemic patients. Furthermore, true negative (TN) indicates that 127 conjunctival images are both normal and correctly predicted by the model to be normal. Based on the matrix confusion, it is also known that there is just one normal conjunctival image that the model wrongly predicts as anemia (False Positive (FP)) and as many as 26 anemic conjunctival images that the model incorrectly predicts as normal (False Negative (FN)). The results of the confusion matrix evaluation provide insight into how well the model can detect anemia. Notably, the model has an accuracy of around 91.1%, which indicates that approximately 91.1% of the conjunctival images are accurately predicted.

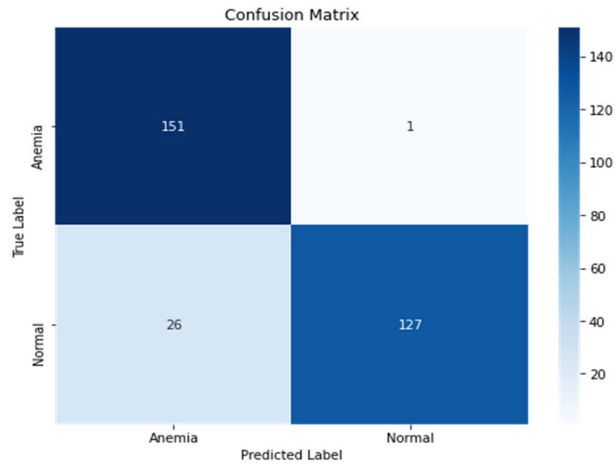

FIGURE 6. The confusion matrix in Scheme 1's best conjunctival image classification model.

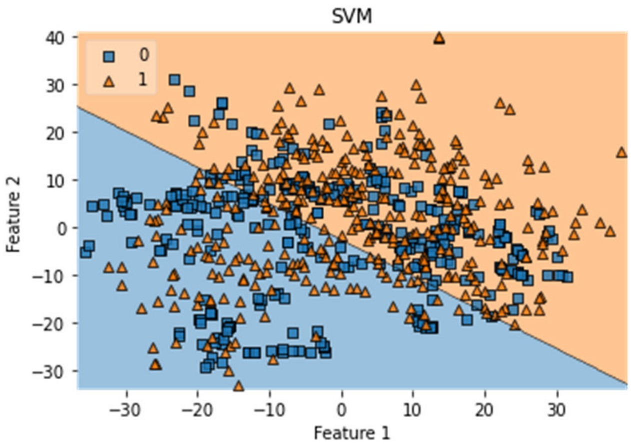

FIGURE 7. Visualization of the SVM algorithm process in conjunction with PCA to identify conjunctival images in Scheme 1.

Following that, the sensitivity value (true positive rate) is around 85.3%, demonstrating that the model does an excellent job of identifying genuinely positive anemia cases. Meanwhile, a specificity of roughly 99.2% implies that the model is quite good at predicting normal cases that are truly negative.

SVM visualization using PCA (Principal Component Analysis) can assist in understanding how the SVM model with a linear kernel distinguishes between anemic and normal classes in two dimensions. PCA is a technique for reducing feature dimensions to improve data visualization. In this situation, we used PCA to decrease the feature dimensions to two and then plotted the results. Figure 7 depicts how the data from the two classes are dispersed on a two-dimensional plane. A good visual separation between these classes may indicate that SVM models with linear kernels efficiently differentiate between conjunctival images with symptoms of anemia and normal ones.

2) CONJUNCTIVAL IMAGE CLASSIFICATION USING THE MobileNetV2 ALGORITHM (SCHEME 2)

The second classification involves the application of the MobileNetV2 algorithm to detect anemia in eye conjunctival image data. Several parameters and configurations are utilized at this stage to configure the MobileNetV2 algorithm. Here are the parameters and configuration used:

1. Learning Rate (Lr): A learning rate of 0.0001 is used in this study. The learning rate is a parameter that governs how many steps the optimization algorithm takes in each iteration when seeking optimal values for the model's weights and biases.
2. Activation: SGD (Stochastic Gradient Descent) is used as the activation function in this study. SGD is an optimization algorithm often used in machine learning to minimize the loss function by updating the model parameters at each iteration.
3. Freezing Layer: This expression refers to the first 70% of MobileNetV2's layer as being frozen. This means that certain layers won't be altered throughout the training phase, preserving the qualities those layers have already learned.
4. Implementation of L2 Regularization: The L2 normal weights component is added to the loss function as part of the L2 regularization overfitting prevention technique. This limits extra weight and makes the model simpler.
5. Output Layer Activation Function (Softmax): In a multiclass classification issue, the softmax function is employed in the output layer to construct the probability distribution for each class. This aids in establishing the model's most likely prediction class.
6. Loss Function (Sparse Categorical Cross Entropy): The Sparse Categorical Cross Entropy loss function is used to calculate how much the model prediction differs from the actual label. The term ''sparse'' denotes that the label is provided as an integer and does not require conversion into one-hot encoding.

TABLE 2. Conjunctival image classification experiment results using the MobileNetV2 algorithm (Scheme 2).

Fold	Accuracy	Sensitivity	Specificity
Fold 1	0.8622	0.811	0.937
Fold 2	0.875	0.861	0.890
Fold 3*	0.895	0.890	0.900
Fold 4	0.856	0.808	0.922
Fold 5	0.853	0.829	0.879

*The best fold in scheme 2.

The model performed best during testing on the third cross-validation (Table 2), according to the findings of the second schema execution utilizing the MobileNetV2 method for its categorization. The model's accuracy score of 0.895 shows how well it accurately classifies all of the data. The model's sensitivity, which measures how effectively it can identify actual cases of anemia, is 0.89. How well the model recognizes genuine normal events is measured by its model specificity, which should be 0.9.

Additional explanation of the confusion matrix (Figure 8) findings in Scheme 2, which employs the MobileNetV2

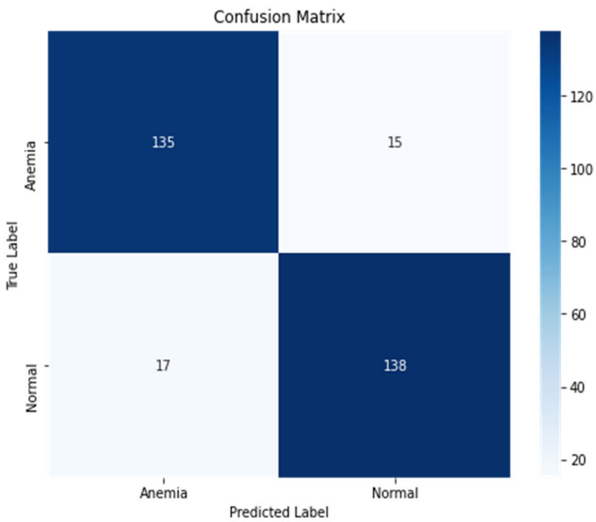

FIGURE 8. The confusion matrix in Scheme 2's best conjunctival image classification model.

algorithm for anemia detection categorization. Following are the outcomes of the confusion matrix in Scheme 2. 135 images are truly in the ''Anemia'' class and were appropriately identified as such. This demonstrates that the model correctly identified 135 images that represented anemia cases (True Positive (TP)). 15 images are mistakenly forecasted as ''Normal'' but belong to the ''Anemia'' class. This suggests that the model missed detecting 15 cases of anemia (False Negative (FN)). However, 17 images that should be classed as ''normal'' are incorrectly predicted as ''anemia'' This demonstrates that the model misclassified 17 normal occurrences as anaemic, resulting in a false positive (FP). 138 images are legitimately characterised as ''normal'' and are suitably portrayed as ''normal.'' This demonstrates that the model was able to detect 138 images that did not depict cases of anemia TN (True Negative).

3) CONJUNCTIVAL IMAGE CLASSIFICATION USING THE SVM+MobileNetV2 ALGORITHM (SCHEME 3)

The third approach in this study employs a hybrid of the SVM and MobileNetV2 algorithms. MobileNetV2 is employed as the initial feature extractor in this method, followed by the SVM algorithm for subsequent classification. In other words, the MobileNetV2 characteristics will be used as input for the SVM model. It is vital to note that the final layer of MobileNetV2 before the flattening layer (perhaps the class-defining layer) will be frozen during this stage. This is done to ensure that the MobileNetV2 features remain stable and do not change during the SVM training process. The size of the output layer before the flattening layer is $7 \times 7 \times 1280$.

The feature data from this frozen layer will also be evaluated by the SVM algorithm to differentiate between ''anemia'' and ''normal'' situations. The training and testing stages will be carried out in the same manner as in the prior scheme, with K-fold validation used to evaluate model performance. The scheme's final findings will show how the combination of SVM and MobileNetV2 affects the classification of anemia detection in the eye conjunctival image dataset. Metrics such as accuracy, sensitivity, and specificity will be used to assess the model's performance in distinguishing between anemia and normal instances.

TABLE 3. Conjunctival image classification experiment results using the MobileNetV2+SVM algorithm (Scheme 3).

Fold	Accuracy	Sensitivity	Specificity
Fold 1	0,9437	0,9155	0,9718
Fold 2	0,9366	0,9577	0,9155
Fold 3*	0,8944	0,8732	0,9155
Fold 4	0,9225	0,9296	0,9155
Fold 5	0,9220	0,9571	0,8873

*The best fold in scheme 3.

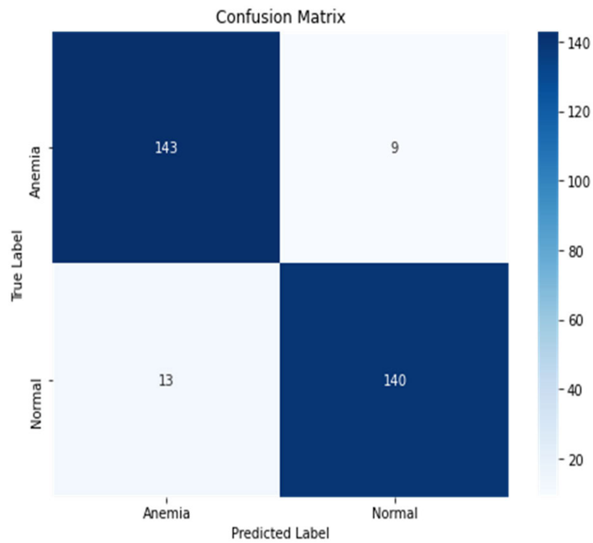

FIGURE 9. The confusion matrix is in Scheme 3's best conjunctival image classification model.

The results of executing the third scheme (Table 3), which combines the SVM and MobileNetV2 algorithms, indicate the model's performance during the testing in the first cross-validation. The model's accuracy of 0.9437 represents how well it properly classifies all data. A sensitivity of 0.915 indicates how well the model detects real cases of anemia. The model's specificity of 0.9718 indicates how well it recognizes true normal instances. The optimal C parameter determined for the SVM algorithm in this scheme is 1.

This confusion matrix (Figure 9) provides into more detail about the classification findings of the third scheme. In this context, the algorithm correctly detects 143 of 152 anemia patients as having anemia (true positive), but incorrectly labels 9 patients as normal while they have anemia (false negative). Furthermore, the model correctly diagnosed 140 of 153 genuinely normal individuals as normal (true negative), but incorrectly classified 13 as anemic when they were normal (false positive). These findings shed light on how well the model differentiates between anemic and normal patients. After performing Scheme 3, namely ''SVM MobileNetV2,''

TABLE 4. Ablation study of conjunctival image classification experiment results using the MobileNetV2+SVM algorithm.

Scheme	With SMOTE+TOMEK			Without SMOTE+TOMEK		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
SVM (Scheme 1)	91	82	99	78	90	29
MOBILENETV2 (Scheme 2)	89	89	90	82	82	80
MOBILENETV2+SVM (Scheme 3) *	93	91	94	83	93	42

*The best model.

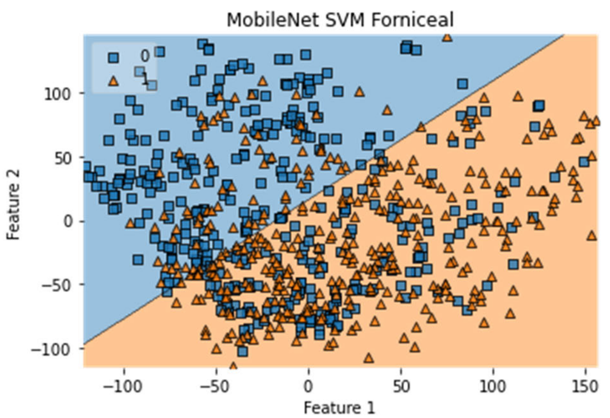

FIGURE 10. Visualization of the SVM algorithm process in conjunction with PCA to identify conjunctival images in Scheme 3.

develop a PCA (Principal Component Analysis) plot for data visualization in the following stage, similar to Scheme 1. After classification using SVM and MobileNetV2, this PCA plot will show how data from two distinct classes—patients with anemia and normal patients—are dispersed in a two-dimensional space.

In Scheme 3, the distribution of eye conjunctival image data is shown in two dimensions using PCA visualization following classification using an SVM and MobileNetV2 combination (Figure 10). The suggested model's ability to discriminate between images in a two-dimensional plane indicating anemia symptoms and normal images is shown in this visualization. Each point in the PCA plot represents an image of the ocular conjunctiva from the dataset. The position of the point serves as a representation of the features of the image following classification using SVM and MobileNetV2. The model can produce precise classifications if there is a distinct division between the points from the anemia and normal classes on the plot.

B. DISCUSSION

To evaluate each scheme's performance and efficacy in detecting anemia, the best test results from each scheme in this study were compared at this point. Table 4 provides a detailed summary of the evaluation's findings, including rating each model's precision, sensitivity, and specificity. According to the evaluation's findings, Scheme 3's SVM and MobileNetV2 model is the most effective. This shows

TABLE 5. Comparison anemia classification results with related work.

Method	Accuracy	Sensitivity	Specificity
Method [13]	82	49	90
Method [30] (based vessels)	-	77	-
Method [30] (based sclerae)	-	73	-
Proposed Method	93	91	94

that, when compared to models from Schemes 1 and 2, the model created in Scheme 3 has the best performance. The Scheme 3 model has the highest accuracy, sensitivity, and specificity metric values when compared to models in other schemes, demonstrating this advantage. From the evaluation results (Table 4) of the three modeling schemes that have been carried out on the detection of anemia in the eye conjunctival image dataset that has gone through the pre-processing and handling of data imbalance stages, the following conclusions can be drawn:

SVM Scheme: The first schema uses the SVM algorithm with a linear kernel. The evaluation results show that the SVM model has an accuracy of 91%, a sensitivity of 82%, and a specificity of 99%. Although the sensitivity is slightly lower, the high specificity indicates that the SVM model is very good at classifying normal conditions. However, the ability to recognize cases of anemia can still be improved.

MobileNetV2 scheme: The second scheme uses the MobileNetV2 algorithm. The evaluation results show that the MobileNetV2 model has an accuracy of 89%, a sensitivity of 89%, and a specificity of 90%. This model has a balanced sensitivity and specificity, but the accuracy can still be improved.

MobileNetV2 + SVM Scheme: The third scheme combines MobileNetV2 with SVM. The evaluation results show that this model has the best performance. The accuracy is up to 93%, the sensitivity is up to 91%, and the specificity is up to 94%. This model has a good balance between the ability to recognize anemia and normal cases and can provide good classification results overall.

Based on the evaluation results, it can be concluded that the MobileNetV2 + SVM scheme has the best performance in detecting anemia on conjunctival images of the eye. This model can combine MobileNetV2's advantages in feature extraction with SVM's ability to classify data, So it can be concluded that this scheme is a method that is proposed and recommended for further analysis Ablation studies are important [80], where the comparison of the three schemes in Table 4 is also an ablation study because it can be seen that the dependence of each method (SVM + MobileNetV2) when the two methods are separated and after being combined, the result is increased detection performance. Data augmentation based on SMOTE and data cleaning from noise with TOMEK also have a remarkable effect. It can be seen in Table 4 that even though MobileNetV2 and SVM have been combined, the detection performance can still improve significantly because SMOTE and TOMEK make the dataset balanced. Apart from comparative ablation studies, it is also important to carry out [81], in this case, the widely-known baselines in the field of the anemia detection method. It should be remembered again that accuracy, specificity, and specificity are the most important measuring tools in medical classification, especially specificity. These results are much better than those of related studies [13] and [30]; see Table 5. Related studies with the same aim for anemia classification also use the same dataset, namely Eyes defy-anemia. It is clear that the results shown from the proposed method have superiority in all three measuring instruments. The classification focus on the palpebral part also influences this. Even if you compare the results of the two schemes, this method is still superior to the method [13], both of which use MobileNetV2. In particular, the sensitivity method [13] is low. It must be emphasized that the positive class becomes a minor class in an unbalanced dataset. Meanwhile, sensitivity is significant in the medical world because it relates to identifying positive data. Meanwhile, accuracy refers more to general results, so if the dataset is imbalanced, these results are inappropriate for reference. A different approach to the method [30] using vessels and sclerae is also no better than the proposed method. This is a finding that the right approach also determines classification performance.

V. CONCLUSION

Based on the results of the research that has been done, it can be concluded that to detect anemia non-invasively through images of the eye conjunctiva, the best scheme is a combination of MobileNetV2 with SVM (SVM + MobileNetV2). This scheme produces the most optimal performance compared to other schemes. The SVM + MobileNetV2 model shows an accuracy of 93%, which means the ability of the model to classify patients overall correctly is very high. A sensitivity of 91% indicates the model's ability to accurately identify patients with anemia, thereby reducing the risk of misdiagnosis. On the other hand, a specificity of 94% indicates the model's ability to recognize healthy patients well.

These results are very promising in a clinical context, as this approach provides an easier and non-invasive way of detecting anemia. Thus, SVM + MobileNetV2 has the potential to positively impact healthcare by enabling early detection and more effective treatment of patients who may have anemia. Although other schemes also show good performance, the SVM + MobileNetV2 combination excels in the balance between accuracy, sensitivity, and specificity, making it a strong choice for the non-invasive detection of anemia via images of the ocular conjunctiva.

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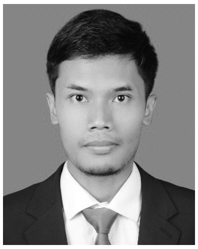

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