Detection and Classification of Neonatal Jaundice Using Color Card Techniques – A Study

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Abstract—In a newborn baby, the particular complication is jaundice. Jaundice is due to many reasons. An increase in the bilirubin level denotes the presence of jaundice. Neonatal hyperbilirubinemia is most common in the first postnatal week. Early prediction and classification of jaundice are essential to reduce the mortality rate. Diagnosis of the disease using computer vision techniques helps to achieve accuracy in prediction and classification. Here, I studied and extracted the information from medical data mining and achieved the goal. It involves examining, analyzing, extracting, selecting, and classifying the features. Finally, it provides treatment suggestions. It enables the physician to perform early prediction and provide appropriate jaundice treatment. Computer vision and machine learning techniques make the process easy and simple. The optimized method of classification increases accuracy. The review provides a detailed description of the diagnosis of neonatal jaundice using the skin region. The entire survey is performed based on their processing steps. Examining a huge number of medical images can reduce the risk. However, the medical images incorporate a huge amount of information about the bilirubin level on the baby's skin, and the increase in the number of images makes their accurate assessment a challenging task. This paper reviews various promising methods developed in computer vision to detect and classify neonatal jaundice. It presents a comprehensive analysis of various approaches. The analysis focuses on the advantages and disadvantages of various methods.

Keywords—computer vision techniques, classifier, color card techniques, deep learning, feature extraction, feature fusion, feature selection, machine learning, medical data mining

1 Introduction

About 80% of preterm infants suffer from jaundice in the first few days of life. Jaundice at the initial stage is nontoxic. The severe stage leads to brain damage and causes kernicterus. Sometimes it also affects the liver cells. The basic reason behind jaundice is the concentration of bilirubin. Jaundice that continues for more than 14 days is considered prolonged jaundice. Around 15% of infants are induced by prolonged jaundice. In principle, medical data is diverse, moral, and statistical. Medical data mining plays a vital role in medical data. Feature extraction and feature selection are carried out to reduce dimensionality and reduce the computation time. The ability and strength of the algorithm are evaluated.

This paper reviews the most recent suggestions to determine and medicate neonatal jaundice. The scope of the study includes exploring various techniques for skin detection, feature extraction, image fusion, feature selection, and classifier construction. Several challenges, such as handling large amounts of data, data and image integration, and image mining with the clinical system, are being addressed. Enhancement of medical data mining will be the objective of many research societies. The feature selection method from computer vision plays an important role in the image of medical data. It includes feature extraction, feature selection, and classification by machine learning. Some of the image preprocessing techniques are implemented on image data before applying machine learning methods to reduce the complexity and make the computation fast, easy, and simple. Therefore, the implementation of computer vision techniques and machine learning methods on medical data helps to provide early prediction and classification. The diagnosis of the disease using these methodologies will boost the accuracy.

1.1 The motivation for the study

The different approaches and components of the review are characterized. The approach deals with the collection of analogous data. Components deal with extracting information from medical data and regulating the scope of the study. In this paper, we derive explanations and aim to analyze based on the medical tasks on particular algorithms and regulations of artificial intelligence. Medical data mining deals with diseases and drugs. With the help of machine learning and computer vision techniques, the prediction model is built by using a classifier algorithm. It gives an exhaustive framework to coordinate the application of medical data mining. The diagnosis is done automatically using data integration. Scalability is essential for a huge amount of data to provide accuracy and efficiency. The workflow of the related work is illustrated in Figure 1.

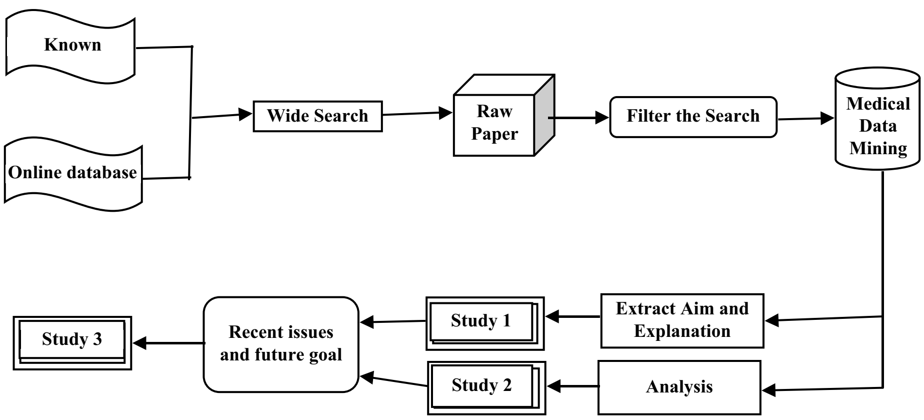

Fig. 1. Plan to gather review papers

1.2 Medical data mining

The organization of the medical tasks is illustrated in Figure 2. Medical data mining consists of three parts, namely: data mining, medical nature, and goal. Data mining extracts the information and builds the model using medical data. The goals are based on improving efficiency, minimizing errors, and reducing computation costs and time. The different sources of medical data are images, test reports, and medical observations. For particular diagnosis and treatment, standardization and integration are required. Different kinds of data are clinical data (text), trial data (numerical), image data (MRI), ultrasonic data (echo), sequential or time-series data (timestamp), signal data (EEG or ECG), and genetic, microarray, and protein data. Here, only the image data is considered. The asymmetry and high dimensionality of image data are essential in medicine. Medical data undergo high risk because it is related to human life. It involves many participants, such as patients, physicians, nurses, and the health care system. Accuracy plays a vital role in medicine. Few diseases require expensive medical tests. Therefore, increasing accuracy and reducing cost are becoming the most common objectives. The medical data undergoes feature extraction and feature selection from computer vision techniques.

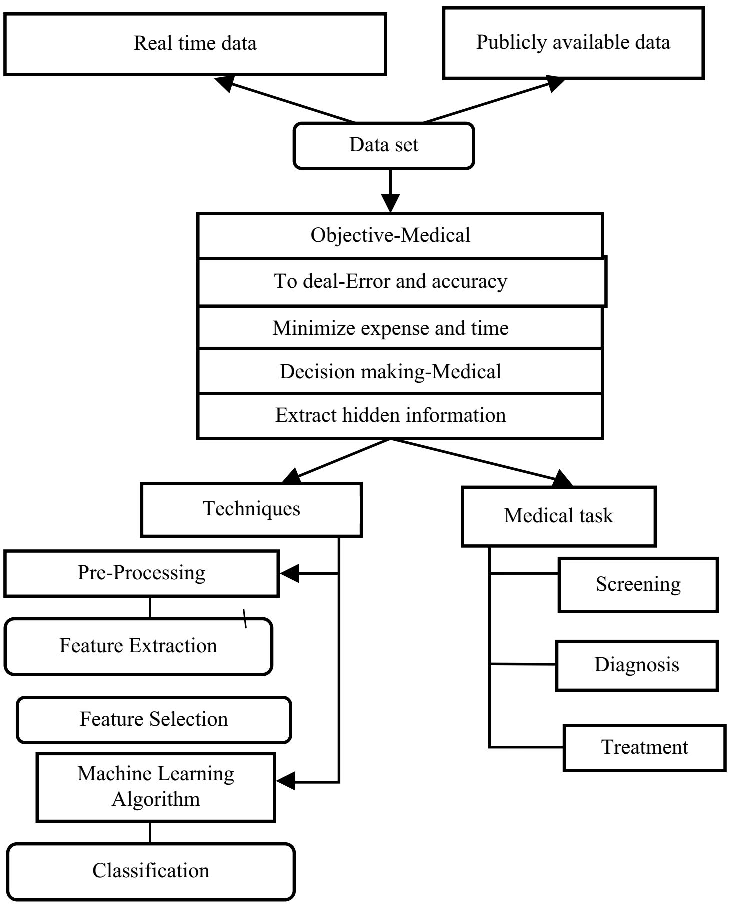

Fig. 2. Organization of the work

2 Related work

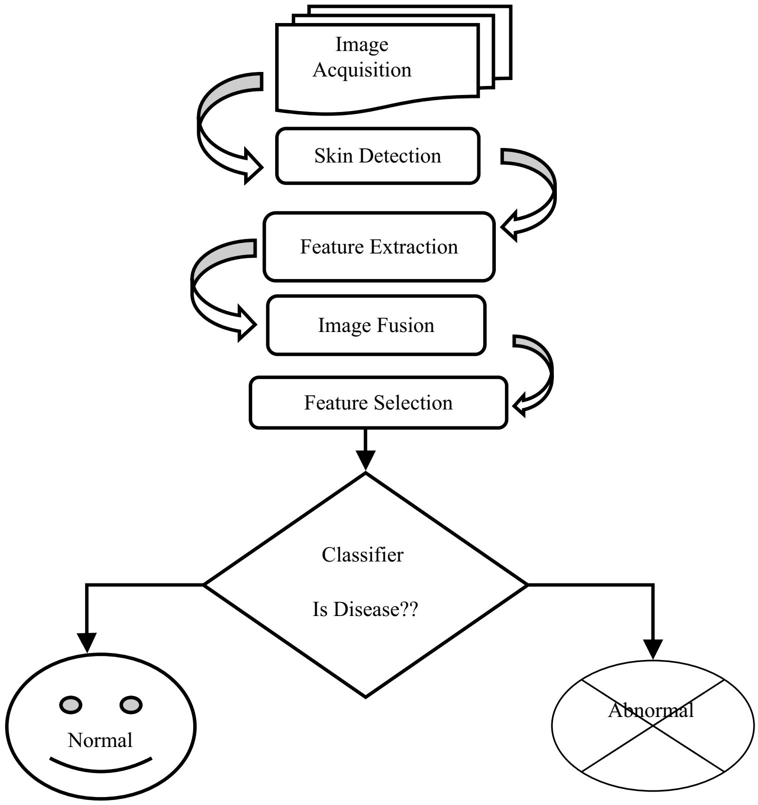

Fig. 3. Steps of pre-processing techniques

Computer Vision combines a variety of factors, including mobile technology, computing power, hardware design, and building new algorithms on both hardware and software platforms. It plays a vital role in image analysis. It is essential for processing medical image data. The processing step is illustrated in the flowchart in Figure 3.

Computer vision provides the following steps.

- Image acquisition: capture the image dataset.
- Skin Detection: Identify the skin region.
- Feature extraction: Dimensionality reduction.
- Image Fusion: Gather highly efficient details from multiple images.
- Feature Selection: Selection of features.
- Classifier: Classifies and labels the dataset.

2.1 Image acquisition

Infants under 1-year-old who have hyperbilirubinemia are considered. Affected newborns make up 60% of the dataset, whereas healthy infants make up 40%. Kaggle, the

UCI Machine Learning Repository, and the Google dataset all contributed to the image collection. Additionally, pictures may be taken using a smartphone or high-resolution digital camera. The digital camera's image is utilized for testing while the publicly accessible dataset is used for training and validation.

2.2 Skin detection

Identifying skin regions in newborn babies is essential in the diagnosis of disease. Skin detection is done by preprocessing techniques. Detecting a skin region by using the color space in the skin model is commonly used. It includes intensity de-correlation. Luminance has very low performance in skin detection. Abbscheddad et al. [1] implemented new techniques in color space along with an error signal. By employing this approach, he minimized the spatial dimensionality from three dimensions (RGB) to one dimension. Improvement in reduction is required due to the computational burden. It is applicable only to hiding knowledge. The Haar wavelet-based skin method was used by Porle et al. [2]. He improves the performance by using six color spaces such as RGB, RGB, HSI, TSL, SCT, and CIELAB. It consists of the decomposition of the wavelet. As the number of color spaces increases, it leads to an increase in computational time and complexity.

The performance of various skin detection algorithms is compared with various measures of the skin-pixel detection algorithm. A.M. Aibinu et al. [3] analyzed some other techniques and evaluated the performance of the artificial neural network-based YCbCr skin recognition. Cb and Cr are adequate for the detection of skin regions. The YCbCr skin-pixel method provides better efficiency than the RGB method. It gives less accuracy while distinguishing between background and skin pixels. An optimal solution with a higher Mean Square Error of 0.0783 is obtained with a maximum accuracy of 0.9610. The crucial skin detection method is to identify whether a single pixel is a skin region or not. HaiquiangZuo et al. [4] implemented a deep learning algorithm to deal with a single pixel. He proved pixel-wise labeling using the Convolution Neural Network. The link between the pixel and its neighbor is obtained by integrating the convolution neural network into a recurrent neural network. CNN focuses on common local features and RCN model dependencies on semantic contextual information. This method detects a skin region with high efficiency.

Endang Juliastuti et al. [5] proposed a methodology to deal with hyperbilirubinemia which causes yellow discoloration on babies' eyes and skin. It is a serious case in the severe stage. It may lead to mental illness or even the end of life. He implemented pre-processing techniques to filter out noise and outliers. He segmented the filtered image using K-means to obtain the baby's skin. The bilirubin level is evaluated by the model of multivariable linear regression. He estimated four different errors, such as error zero, positive error, false positive, and false negative. The risk zone is defined by error. In the case of the breakdown of red blood cells, the yellow discoloration deposits on the liver. In the severe stage, it affects the liver and brain. Risk is based on the bilirubin level of infants. The image was captured using a smartphone without a flash. Uma et al. [6] use a color calibration card. It consists of eight distinct colors. She analyzed the image using the MATLAB tool. She implemented the color balancing method, region-based segmentation, and point-based segmentation techniques. It is feasible.

Due to insufficient testing rules and a lack of benchmarks, skin detection is a challenging task in skin detection. Nowadays, CNN is mainly used for segmentation with insufficient ground truth. Therefore, Alessandra Lumini and Loris Nanni [7] introduced a fair comparison among techniques. Parameters included are human characteristics, condition of acquisition, skin painting (makeup or tattoo), and complex background. He uses 10 datasets with 10,000 labeled images. Based on the taxonomy strategy, skin detection techniques are classified.

The taxonomy strategies are:

- Consideration of the presence or absence of the preprocessing step.
  - Color correction.
  - Illumination Cancellation.
  - Dynamic Adaptation.
- Concerning the color space.
  It deals with selecting the appropriate skin color model.
  - RBG stands for Basic Model.
  - Perceptual model (HIS, HIV).
  - Perceptual uniform model (CIE-Lab, CIE- Luv).
  - Orthogonal model (YCbCr, YIQ).
    Among the four models, orthogonal models minimize correlation/redundancy. It is well adapted for skin detection.
- Examine the problem formulation.
  It deals with the segmentation of input image data.
  - Region-based segmentation.
  - Pixel-based segmentation.
- Comparison between methods of pixel classification.
  - Rule-based approach (defining skin color by explicit rule).
  - Machine learning approach (using parametric/non-parametric methods to evaluate pixels).
- An analysis of the classifier model for the machine learning approach.
  - Statistical Method (Bayesian Rule – parametric method).
  - Neural network model (with color and texture knowledge, the color image is segmented).
  - Adaptive method (obtains a particular condition by turning the parameter).
  - Diffusion-based model (Enhance the classifier efficiency by considering the neighbor pixel).
  - Hyperspectral model (handle acquisition device).
  - Mixture techniques. (a collaboration of various machine learning techniques).

Harsha B K and Dr. G Indumathi [8] have done a survey related to skin detection in images using a pattern-matching algorithm. They obtained three essential contributions. They are.

- Integral image – Image representation is done by novelty. She implemented speedy feature estimation. The Haar basis function is invoked after computation.
- The construction of a skin classifier.
- Cascade the complex classifier to maximize the detection speed.

2.3 Feature extraction

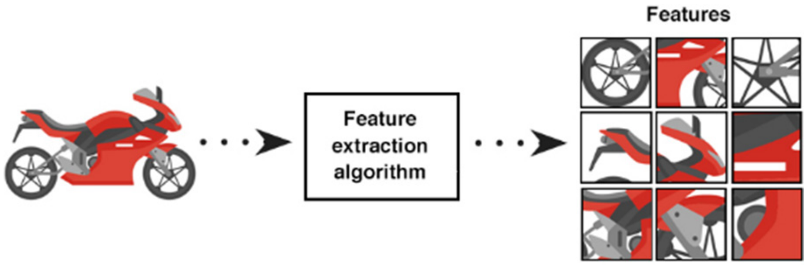

Fig. 4. Feature extraction methodology

A perceptive methodology is required to make the diagnosis of a disease, a process that is quick and accurate. Feature extraction plays a vital role in the process. Feature extraction of converting raw data into various features. Features are processed while sustaining the knowledge in the original dataset. Figure 4 illustrates the operation of feature extraction. Feature extraction requires a huge amount of information to process the result. With the support of a physician, the accuracy can be calculated. Aimin Yang et al. [17] implemented a convolution neural network to perform feature extraction on medical images. It increases the robustness of the medical image. The accuracy is increased by implementing two convolution models. They are Dense Net and Xception. The model is trained with a large number of datasets to extract the features of the medical image. A new approach to local binary pattern feature extraction has been introduced. It is based on image rotation variation. It provides powerful technical encouragement for the self-checking system and diagnosis system. Among the deep learning algorithms, the convolution neural network (CNN) achieved the goal of diagnosing disease from medical images. DimpyVarshini et al. [18] trained the model with a huge amount of data. It is essential for classification performance. It is used to classify normal and abnormal medical images. Detection is performed by the Densely Connected Convolution neural network. It is denoted as "DenseNet-169". To remove gradient complications, all layers in this method are connected with the same feature size. Generic features are generated in DenseNet-169.

The deep learning method deals with feature extraction and classification. It is necessary for processing medical images. Xu Chen et al. [19] proposed deep learning to diagnose medical images. He studied the feature by using a deep neural network for feature extraction. He extracted Glutamate cysteine ligase modifier features (GCLM) and local binary pattern (LBP) features from X-ray images. He classifies the feature using a support vector machine (SVM). The basic kernels are RBF, poly and sigmoid. To get the nonlinear mapping φ(x), the kernel SVM starts with a kernel $K(x,x')$. He improved his performance and accuracy by using multi-dimensional data and achieved a 0.455. This method is excellent compared to other approaches. An easily perceived disease by the eyes is jaundice. An analysis using machine learning and computer vision helps the physician provide early treatment. In jaundice, measuring the bilirubin levels is important. It is invasive, costly, and time-consuming. By employing yellow colorization on infant skin, computer vision techniques provide a wide platform to measure the bilirubin. It is efficient and quicker. Md. Messal Monem Miah et al. [20]

did feature extraction based on the feature vector. It consists of a statistical feature, an RGB histogram feature, an HSV histogram feature, and the YCbCr histogram feature. Sclera segmentation based on the adaptive thresholding method is introduced. It is unresponsive to lightning conditions.

Jaundice in the newborn is familiar in the first week of life. Mustafa Aydin [21] proposed a method to measure jaundice periodically without any blood tests. It allows physicians to diagnose the disease and prescribe early medication. He considers the grouping of babies based on age and the affected babies' age. Image processing techniques are implemented on medical images. Segmentation, white balancing methods, and pixel similarity are familiar. Feature extraction includes color map transformation and feature calculation. It gives 85% accuracy in the bilirubin result, and the complication rate is 85%. It is essential to fuse multiple images to generate an accurate fused image. Deep learning succeeds in analyzing multimodal medical images and recognizing the images. Yan Xu [22] studied deep learning methods to analyzed them. In the analysis, medical image feature extraction is crucial. The most possible ways to perform the analysis are DBM and DBN, CNN, SAE, CNN, and GAN, respectively. It plays a vital role in image segmentation, classification, and synthesis. Introducing bid data is an advance in analyzing multimodal medical features.

Face recognition is an important factor in a few medical applications. It is a challenging complication in computer vision techniques. Complication due to the complex essence of the face region. Afshan Latif et al. [23] did 3D face recognition by implementing an intrinsic coordinate system (ICS) based approach. The feature extraction is done by the deep learning method of AlexNet. Performing feature extraction using deep learning provides the advantage of dealing with large-scale datasets and maximum computational speed. Alok Sarkar et al. [24] implemented a genetic algorithm for feature extraction. The implementation is easy and simple. Instead of processing the medical data as a whole, it is necessary to extract the relevant features to make the computation faster. Some of the irrelevant features are filtered using preprocessing techniques. Feature pruning maximizes the classifier's generalization. It will reflect on classification accuracy. The specificity, accuracy, and sensitivity obtained through the method are 100%, 98.3%, and 98%, respectively.

2.4 Image fusion

Combining two or more pixel images will generate a high enlightened fused image. It gives more information than the source image. Pixel-level image fusion is essential in image fusion. It deals with different focusing and depth of field of the same image. Multi-focus image fusion fuses all source images together to produce a high-resolution fused image. It can be used in the transform and the spatial domain methods. The work is based on the spatial domain. It is classified into a block-based method, a pixel-based method, and a region-based method. Siamese multi-scale feature extraction provides an effective convolution filter. It helps to achieve better accuracy. Hafiz Tayyab Mustafa et al. [9] contribute to multi-scale CNN to gain multi-focus image fusion, a siamese multi-scale feature extraction module to get the most accurate input image feature, and no reference feature. He compares the computational performance with other methods such as IM, GF, MSWG, BF, and CNN. In comparison, CNN provides better efficiency than others. He proposed MFIF-based MSCNN. The fusion image by the multi-scale method provides image restoration accurately. The performance is estimated by quantitative and qualitative validation. The medical image fusion method helps doctors figure out what's wrong with a patient, gives continuous treatment, and does more planning and guiding for surgery. It is explained in Figure 5.

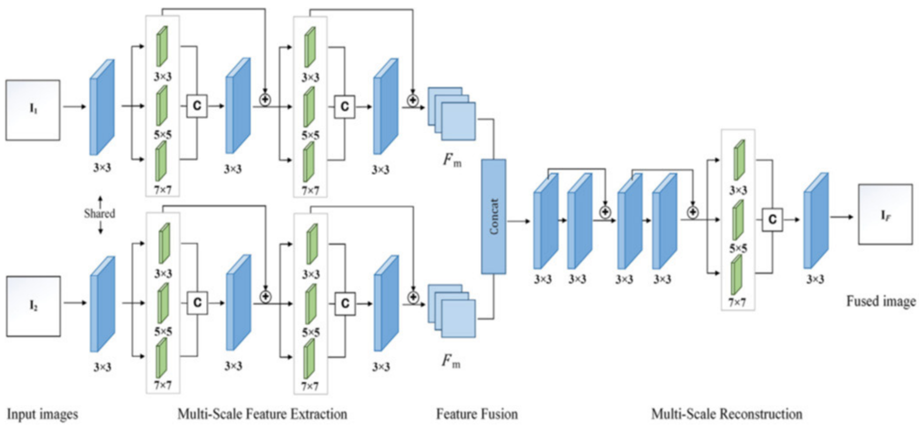

Fig. 5. Medical image fusion

A multi-layer concatenation fusion network (MCFNet) was proposed by Xuecan Liang et al. [10]. It is used for image reconstruction by feature mapping, feature extraction, and feature selection. Enhancement in visual quality and objective estimation is achieved by this method. He applied the techniques to CT and MRI images. MCFNet reduces the mean square error. It enhances objective validation. The loss function should be optimized and also be able to implement a robust fusion network. The fused image is transparent and efficient. Di Gai et al. [11] implemented multi-medical image fusion on both color source images and grayscale images. He used the NonSubampled-Shearlet Transform (NSST) to divide the source image into low and high-frequency bands. He used the technique to destroy specific features and enhance them so they secured energy efficiently. Edge preservation is done by EP-PCNN. It provides better performance.

The optimal quality image is obtained by fusing one or more images. Along with NSST and EP-CNN, Li Yin et al. [12] proposed sparse representation (SR), Max Li Fusion rule to elaborate the feature information in the low-frequency component. An NSST inverse transform is implemented to re-organize high and low-frequency components. It reduces complexity. Kai Jian Xia et al. [13] proposed the Gaussian filter and Laplace Transform of Gaussian (LoG) to partition the source image into different sub-images. It is performed in the first layer of the deep convolution neural network. They built a basic functional unit by using a HeK-based algorithm on the remaining layer. The process of decomposing images is based on high and low frequency. Finally, it is fused to the obtained fusion image. The experimental result gives better performance and enhances quantitative parameters. He speeds up the performance and generates fusion quality.

Multi-scale medical images provide some essential knowledge. They support the physician in the diagnosis of the disease and provide the treatment. Zhaobin Wang et al. [14] introduced the Laplace pyramid (LP) division and adaptive sparse representation (ASR). It helps to reduce noise and redundancy and blocks effects at high frequencies. It is an efficient fusion method for medical images. Medical images such as X-ray, CT, MRI, and SPECT are considered. SR improves human visualization. Image fusion efficiency has been developed. The characteristics of the fused image are maximized to perform a better diagnosis of disease. The direct fusion method generates low contrast and high computation effort. To overcome the complications, Padmavathi K et al. [15] proposed total variation (TV-L1) to generate an efficient fusion image. This method is based on particle swarm optimization (PSO). It deals with edge information and contrast of a fused image. The proposed method is robust. Fusion image sharpness is developed. It is objectively and visually efficient. It is a computer vision technique to deal with several challenging tasks in image fusion. Manjit Kaur and Dilbag Singh. [16] improve efficiency by implementing a deep belief network. Feature extraction is done before the image fusion. After image fusion, feature selection is performed on the fused image. He has done the image fusion using a deep belief network formed using machine learning techniques. Nowadays, computer vision techniques make medical image processing automatic and enhance image processing. A deep belief network eliminates fog, smog, and haze. It effectively turns off the hyper-parameter. The efficiency of preserving an informative image is achieved.

2.5 Feature selection

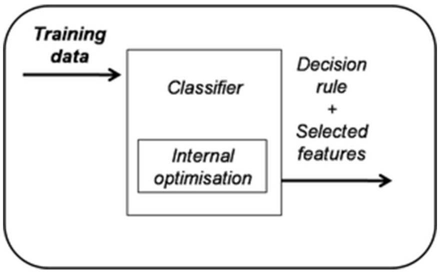

Fig. 6. Hybrid feature selection method

Feature selection is essential for medical image diagnosis. It deals with computation costs. It reduces dimensionality and processes extraneous or excessive features. Feature selection is carried out to protect the resource, make the process simple, and maximize its accuracy. The hybrid model combines both the filter method and the wrapper method to overcome the disadvantages of both the filter method and the wrapper method as shown in Figure 6. It deals with a specific model. It is similar to a wrapper except that the classifier is integrated with the feature selection algorithm. Mohamed Abdel-Basset et al. [25] discovered Hybridized Harris Hawks optimization, based on simulated annealing (SA) and bitwise operations to find the optimal feature subset. It deals with the binary problem and shows excellent performance in balancing exploitation and exploration. It departs from local optima. He maximizes diversity. Feature selection generates an essential feature to improve the classification. It plays a vital role in dealing with accuracy and performance. Shanthi S and Rajkumar N [26] proposed a novel method of feature selection. The optimal feature subset is determined by using a modified stochastic diffusion search (SDS) algorithm. It reduces the superfluous and increase the importance. This method increases the learning system. Feature selection deals with ranking, selecting, and screening. The ranking will grade the optimal solution. Selection deals with generating an optimal feature subset and screening to eliminate undesirable features. The hybrid method of feature selection searches for the optimal feature subset.

Mesut Togacar et al. [27] implemented the Minimum Redundancy Maximum Relevance (MRMR) feature selection method to generate adequate features. He achieved a maximum accuracy of 99.51%. The model is very efficient for the diagnosis of disease. Here the classification is analyzed individually. He trained the model using an augmentation approach. It applies to CT-based medical images. It is compiled into the GPU environment for better performance in time and speed. The method is used along with the combination of K-NN and AlexNet with an accuracy, sensitivity, and specificity of 99.51%, 99.32%, and 99.71%, respectively. Mesut Yogacar et al. [28] considered Recursive Feature Elimination (RFE) for the study of feature selection with the support of the hypercolumn approach. It achieved AlexNet and VGG-16 network generalization. It improves the discriminative capacity of classification. The combination of SVM with RFE minimizes feature set dimensionality and provides a better result. Feature selection deals with the "curse of dimensionality". Jiangzhang Gan et al. [29] proposed a supervised learning method based on feature selection along with a Self-Paced Regularizer (SP-Regularizer) to bind the model. The ability to generalize is obtained by training the model with highly confidential samples. Implementation of $l_{2,1}$ – norm maximizes performance. It offer better performance than other methods. The sparse feature selection theory is used to select a valuable sample feature. It combines sparse learning and SP- learning. It chooses the feature from the MRI scan. Vemula Vinay Kumar et al. [30] to implemented KNN- GA. This method is the hybrid feature selection method. It favors a relevant and meaningful feature of the medical image. It is implemented during classification to minimize the computation time. It helps to improve classification accuracy. KNN-GA minimizes the repetition in the input picture element and explains the importance of input and output picture elements. GA selects the feature subset as a chromosome and it is given to KNN. KNN operates each chromosome as a mask and defines fitness for each chromosome. Throughout the process, GA finds the optimal feature subset.

Grey Wolf Optimizer (GWO) in nature is a hunting and leadership method. GWO gives slow convergence and minimum precision. Therefore, Modified Binary GWO (MBGWO) is proposed by El-Sayed M et al. [31] based on Stochastic Fractal Search (SFS). It is determined to prefer features with a balance of exploration and exploitation, respectively. Modification is done by implementing exponential on a number of epochs of GWO. It helps to maximize the diversity and the search space. SFS provides an optimal solution. The classification is done along with feature selection. It is performed by KNN to qualify the selected subset. Basic GWO provides flexibility, and the possibility to avoid local optima. A better computer vision method is applied to medical images to undergo computer-aided diagnosis (CAD). It is based on dimensionality reduction and processing of irrelevant features. Feature selection plays a vital role in feature reproducibility. Nicolas Georges et al. [32] undergo the FS-Select framework. It provides a relationship between feature selection methods. It is based on feature stability, average accuracy, and reproducibility power. It is efficient at prediction. Here, he determines the most reproducible optimal best-fit feature subset.

Feature selection reduces complexity in computation. Mehrdad Rostami et al. [33] proposed a multi-objective feature selection method based on the PSO method. It deals with the graphical representation of original features, calculates the feature centralization of all nodes, and performs feature selection based on the PSO search process. In healthcare, it is essential to make a decision based on diagnosis, scanning, observation, medication, prediction, and clinical administration. In the proposed method, the fitness function is used without the learning rule to estimate the feature subset. The validation includes feature subset size, individual index, and similarity, which improves convergence. The feature subset has low similarity and high dependency. Warda M. Shaban et al. [34] implemented a Hybrid Feature Selection methodology consisting of two phases, such as an accurate selection phase and a fast selection phase. Accurate selection has been done by the wrapper method and fast selection by the filter method. A genetic algorithm is utilized to perform feature selection.

2.6 Classifier

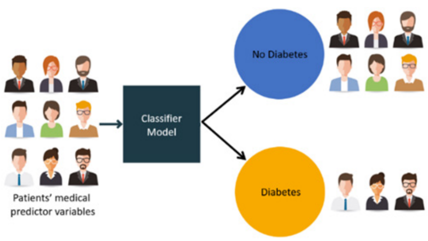

Fig. 7a. Model of the classifier

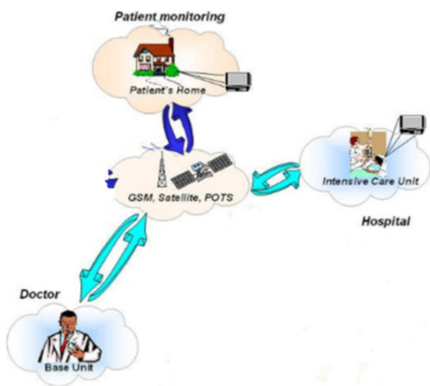

Fig. 7b. VH-Doctor

Classifiers assign class labels to input data as shown in Figure 7a. Binary classification is important while diagnosing medical images. This method helps to identify, validate, and observe whether the given medical image is affected or not. B. Venkataramanaiah and J. Kamala [35] proposed a KNN classifier to diagnose the disease. The KNN classifier provides higher accuracy. Classification is done based on a similarity measure. KNN is a common method in regression and classification methods. The accuracy is based on the k-value. It lies between 1 to n. It is essential to diagnose people living in rural areas. VH-Doctor uses the KNN classifier to find abnormal patients. It takes a minimum period to diagnose the disease, which supports early treatment. Proposing VH-Doctor is creative and the function of VH-Doctor is given in Figure 7b.

Previously, images were retrieved once from the dataset to perform classification. D. Benyl Renita and C. Seldev Christopher et al. [36] obtain the image multiple times.

They implemented the GWO-SVM method to classify a query image from the query database. GWO gives a clear optimal parameter to the SVM classifier. Image query retrieval improves performance and accuracy. The query image database is obtained by processing input medical images with the HSV color space. It is an optimized based classification. P. Indra and M. Manikandan [37] implemented Unsupervised Test Vector Optimization (UTVO) to classify medical images. It is an efficient method for deciding on the clinical system. Improvement in mammogram images is performed. Texture feature selection is done by a Multilevel Tetrolet Transformation-based feature. The UTVO classifier determines and observes the performance without any adjustment. It gives a better result. It is essential in diagnosing a medical image with a minimum complexity of time. It reduces the performance. Diagnosing the medical image and classifying the disease is subject to a great dispute. Emmanuel Eragbe Sule [38] did classification based on the training set, testing set, and evaluated data. He classified the fields using MATLAB. ANN is a binary classifier. It helps to identify whether the disease is present or not. He obtained a maximum accuracy of 98.7%.

Machine learning consists of multi-stage classifiers such as Support Vector Machine (SVM), Naïve Bayes (NB) classifier, and K-Nearest Neighbor (KNN) to make the classification more accurate and efficient. A multi-stage classifier provides the output of one classifier as an input to another classifier. With this approach, the disadvantage of one classifier is overcome by the other classifier. K.R. Kruthika et al. [39] implemented a multi-stage classifier. The first stage classifier is the NB classifier, and the second stage is the SVM and KNN classifier, respectively. It provides a better result and better retrieval speed. In the multistage classifier, the first stage of the classifier plays a vital role in constructing the classifier. Some tools, like CNN, are cheap and widely distributed. It is only applicable to the limited dataset. Shiv Gehlot et al. [40] enhance the model for the application of large datasets. It deals with the complexity between normal and affected cells. They implemented SDCT-AuxNet (θ). It is a two-classifier model. The main classifier consists of condensed CNN and the supplementary classifier is Kernel SVM. CNN extracts features from bilinear pooling. Kernel SVM adopts a spectral-averaged feature. There is a high risk of subject-level instability. This method provides an increase in error compared to the affected subject. Classifiers provide wonderful achievements in affecting medical data. There is controversy in the case of normal medical data.

The World Health Organization (WHO) recently announced that the mortality rate has increased in the last few decades due to improper diagnosis of treatment. Gopi Kasinathan et al. [41] implemented an Enhanced Convolutional Neural Network (E-CNN) classifier to obtain better performance in the diagnosis of the disease. The efficiency is measured by adopting nodule graphs. They introduced three convolution neural networks (CNN) and improved efficiency. D. Ramamoorthy and P.K Mahesh et al. [42] detect the brain tumor using Whale Harris Hawks Optimization (WHHO), which is coordinated with the Whale optimization algorithm (WOA). In diagnosing disease, accuracy is efficient to reduce the death rate. Detecting the hidden subject in the data set is important. There is a need to enhance the image quality. WHHO-WOA influences the benefits of both optimization and provides improved performance. The analysis is done based on sensitivity, accuracy, and specificity. A hard mining strategy obtains a false-positive reduction efficiency. Yuyun Ye et al. [43] implemented V-Net and High-Level Descriptors based on SVM classifiers to enhance FP reduction. The novelty of SVM is that it includes a wavelet feature. It uses multiple classifiers in parallel. It provides more predictable information for the physician. It is essential in most medical applications. Virupakshappa and Basavaraj Amarapur [44] implemented an optimized Artificial Neural Network (ANN) Classifier along with the Whale providing excellent results.

3 Comparison table of computer vision techniques

The comparison analysis is performed based on the various methodology of the workflow. The analysis is done on the merits and demerits of various techniques.

3.1 Skin segmentation

The skin portions of the photos are brighter than the rest of the image, so they may be distinguished from the background using a thresholding technique. A stable threshold value cannot be established since multiple photos of various persons with various skin tones must be processed. To arrive at the ideal threshold value for each run, an adaptive thresholding procedure is needed since persons with various skin tones have varied likelihoods. Skin segmentation is essential for the diagnosis of disease. The comparison analysis of various segmentation techniques is given in Table 1.

Table 1. Comparison analysis of various skin segmentation techniques

Cite	Algorithm	Pros	Cons
[1]	Orthogonal Color Space	– Color space along with signal error. – Reduce space dimensionality. – Hide information.	– Computation burden.
[2]	Wavelet transform	– Increase accuracy.	– Complexity. – More computation time.
[3]	ANN-YCbCr skin recognition	– Better Performance. – Maximum MSE. – Increase accuracy.	– Expensive based on computation complexity.
[4]	CNN-RCN model	– High efficiency. – Increase scalability. – Pixel-wise labeling.	– The COMPAC dataset consists of a large number. – Low-quality images.
[5]	K-mean	– Estimate risk zone	– Less prediction. – Improvement in accuracy is required.
[6]	Region-based segmentation. Point-based segmentation.	– Feasible.	– Computation cost. – Time complexity.
[7]	Deep learning CNN model	– Outperformance. – No retraining. – No ad hoc optimization.	– Expensive. – Lack of color consistency problem. – Should improve robustness.
[8]	Viola-Jones	– Maximize speed. – Efficient classifier.	– Presence of outlier. – Less robustness.

3.2 Image fusion

Medical image fusion is the process of registering and integrating numerous pictures from one or more imaging modalities in order to maximize the clinical usefulness of medical images for the diagnosis and assessment of medical issues, improve imaging quality, and minimize randomness and redundancy. In order to solve medical difficulties that are represented in pictures of the human body, organs, and cells, medical image fusion incorporates a wide variety of approaches from image fusion and general information fusion. The use of imaging technology for medical diagnoses, research, and historical recording is expanding in popularity. The various techniques of medical image fusion are analyzed and their comparison is illustrated in Table 2.

Table 2. Comparison analysis of various image fusion techniques

Cite	Algorithm	Pros	Cons
[1]	Multi Focus Image Fusion - Multi-scale CNN	– Extract more accurate image restoration – High efficiency.	– Limited source image – Less robust and generic. – Not applicable to moving objects.
[2]	Multi-Layer Concentration fusion network	– Enhance objective validation and visual quality.	– Lack of robustness. – Optimization of the loss function is required.
[3]	Edge preservation - PCNN	– Superior. – Increase visual performance. – Update objective validation.	– Applicable only in the NSST domain. – Less information in the low-frequency component.
[4]	Pulse Coupled Neural Network.	– More Source images. – Elaborate information details in low-frequency components. – Reduces Complexity.	– Limited focus range. – improve parameter selection. – Less Medical application moderate efficiency.
[5]	Deep Convolution Neural Network.	– Faster. – Better fusion quality. – Better result. – Improvement in the quantitative parameter.	– Fusion rule should be done manually.
[6]	Laplacian pyramid	– Minimize noise/ redundancy at high frequency. – Efficient for medical image fusion. – Improve human visualization. – Improve accuracy.	– Improvement in performance is required.
[7]	Total variation (TV-L1)	– Less information distortion. – Boost up visual effect. – Robust. – Improve sharpness.	– Increase computation time. – Complexity.
[8]	Deep belief network	– Outperformance. – Preserve the informative image effectively. – Reduce Redundancy.	– Limited medical application.

3.3 Feature extraction

Typically, medical data sets are tiny and contain a high degree of dimension. An analysis with too many attributes will be less effective and not necessarily more accurate, whereas a model with too little data would be less stable. When the data set is tiny, the best subset of characteristics must be extracted in order to improve analytical performance. Table 3 describes the comparative analysis of various feature extraction techniques involved in medical data study.

Table 3. Comparison analysis of various feature extraction techniques

Cite	Algorithm	Pros	Cons
[1]	Convolution neural network.	– Increase robustness. – Self – Checking system.	– Computation cost and time.
[2]	DenseNet-169	– Eliminate Gradient complication – Generate generic feature.	
[3]	Depth neural network- SVM	– Automatic reading – Performance – Accuracy	– Large error – Analogous to a black box – Lack of robustness
[4]	Random forest	– Efficient. – Quicker. – Noninvasive technique	– Applicable only for adult – Limited dataset
[5]	Color map transformation and feature calculation	– Non-invasive method. – Unique, Novel Software, High quality and optimal. – Short processing time.	– More complication rate
[6]	Deep learning	– Improved accuracy.	– Limited number of training samples
[7]	Alexnet	– More time consuming for large scale data.	– computational cost
[8]	Genetic algorithm	– simple, easy implementation. – more accuracy and sensitivity	– Expensive software.

3.4 Feature selection

Both dimensionality reduction and classification depend on feature selection. Because it removes pointless attributes, feature selection boosts the classifier's accuracy. Medical data mining is different from ordinary data mining because medical information has various properties. The majority of disorders require many tests to be accurately diagnosed, which makes it pricey. By focusing on the variables that are truly crucial for illness prediction, we may use data mining techniques to cut the cost of diagnosis by skipping several procedures. The various feature selection is analyzed and illustrated in Table 4.

Table 4. Comparison analysis of various feature selection techniques

Cite	Algorithm	Pros	Cons
[1]	Hybrid Harris Hawks optimization algorithm with bitwise operations and simulated annealing (HHOBSA).	– Balancing exploration and exploitation. – Depart from local optima. – Maximize diversity.	– Complexity in structure. – Improvement in performance is required. – Need to reduce the time burden.
[2]	Modified stochastic diffusion search (SDS) algorithm	– Better level of performance. – Minimize redundancy. – Maximize the relevance – Determine the optimal feature subset. – Better accuracy. – Optimize classifier.	– Low order relationship. – Mathematical claim about the simple program is difficult.
[3]	Minimum Redundancy Maximum Relevance (MRMR)	– Faster and better result. – Time and speed efficient	– Computation cost. (GPU Environment). – Limited dataset.
[4]	Recursive Feature Elimination (RFE) -SVM	– Enhance discriminative capacity. – Reduce the misdiagnosis rate. – Improve classification. – Reduce dimensionality.	– Limited medical application – Need to concentrate on the binary problem.
[5]	KNN-GA	– Less computation period. – Enhance accuracy. – Reduce redundancy. – Optimal subset.	– Complexity in structure. – Improvement in performance is required. – Need to reduce the time burden.
[6]	Modi_ed BinaryGWO (MbGWO) based on Stochastic Fractal Search (SFS)	– Achieve exploration and exploitation balance. – Increase search space – Increase diversity.	– Applicable in the discrete problem. – Need to concentrate on the binary problem.
[7]	FS- Framework.	– Feature stability – Prediction accuracy – Feature reproducibility power.	– Low order relationship. – Mathematical claim about the simple program is difficult.
[8]	Multi-objective feature selection method based on PSO method	– Increase performance. – Improve effectiveness. – Enhance convergence.	– Parameter Optimization is required

3.5 Classifier

Predicting the class of a set of data points is the process of classification. A classifier in machine learning is an algorithm that automatically groups data into one or more “classes” or categories. Classes are sometimes referred to as targets, labels, or categories. Numerous application fields, including scientific research, medical diagnosis, weather forecasting, credit approval, consumer segmentation, target marketing, and fraud detection, have effectively used classification. The comparison analysis of various classifiers required for medical diagnosis is discussed in Table 5.

Table 5. Comparison analysis of various classifier techniques

Cite	Algorithm	Pros	Cons
[1]	KNN	– Higher accuracy. – Simple implementation. – Less time-consuming.	– Improvement is not critical
[2]	Grey Wolf Optimization-Support Vector Machine (GWO-SVM)	– Better performance. – Better accuracy.	– weak performance in eliminating the disease in healthy medical data
[3]	Unsupervised Test Vector Optimization (UTVO)	– Very less time complexity value.	– Not applicable to object recognition in video processing
[4]	ANN	– Maximum accuracy.	– Computational Cost.
[5]	Multistage classifier – NB, SVM and KNN classifier	– Better accuracy. – Outperformance. – Better retrieval speed.	– More computation time and space – Expensive
[6]	Deconvolutional CNN – Kernel SVM	– Robust to subject-level variability. – Excellent efficiency in predicting disease in unhealthy medical data	– weak performance in eliminating the disease in healthy medical data
[7]	Enhanced Convolutional Neural Network	– High potential diagnosis.	– Not applicable to object recognition in video processing
[8]	WHHO-WOA	– Simple implementation. – Outperformance.	– Need to concentrate on the binary problem.
[9]	V-Net and High-Level Descriptor Based SVM classifier.	– more reliable	– Improvement is not critical
[10]	Adaptive ANN- WOA	– Better accuracy	– Computation cost

4 Estimation of bilirubin level

Bilirubin results are obtained by a blood test. It is an invasive technique. The bilirubin value is evaluated from the regression output. Mustafa Aydın et al. [21] proposed an estimated threshold value for each trail. The difference between the maximum threshold value and the minimum threshold value is the final value of the bilirubin level. It is essential for the detection of neonatal jaundice. The validation of the evaluated bilirubin values and blood results is estimated. The similarity ratio is calculated. At the significance, $p>0.006$ provides a correlation of 0.83 between bilirubin results and blood results. ROC curves are implemented to estimate the accuracy of the bilirubin level. The cut-off threshold is obtained by the F-statistical test. It is optimal, time-consuming, and of better quality. Jaundice forms a yellow discoloration on the skin. It is determined by the level of bilirubin. It is done with different color shades. This method is a non-invasive technique. It is an optical approach. Each color shade represents the bilirubin level as shown in Figure 8. Fitzpatrick shades denote the human skin tone as shown in Figure 9. Asyraf Hakimi Abu Bakar et al. [45] estimate the bilirubin level with a bilirubin reference card. Each level of concentration denotes the corresponding bilirubin level as described in Figure 10. Based on the level, the respective severity level can be determined. It ranges from B1 to B4. This method is a non-invasive technique. It is an optical approach. Each color shade represents the bilirubin level as shown in Figure 8. Fitzpatrick shades denote the human skin tone as shown in Figure 9.

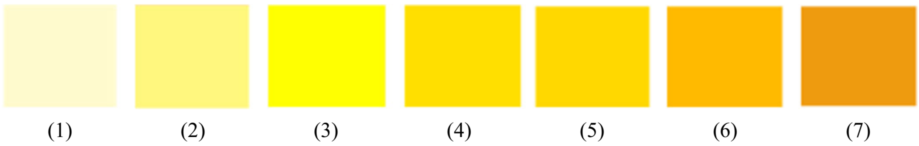

Fig. 8. Yellow shades code (1 - FFFFEE, 2 - FFFF06, 3 - FFFF00, 4 - FFEF00, 5 - FFD300, 6 - FFD700, 7 -DAA520)

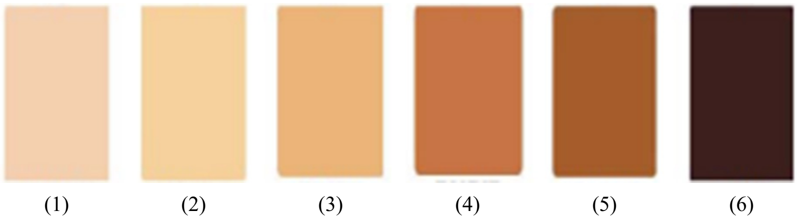

Fig. 9. Fitzpatrick color code (1- FFE5CC, 2-FFCC99, 3-FFB266, 4-E89F5F, 5-CB7E3B, 6-331900)

Yellow shade grade	Bilirubin level (mg/dL)	Treatment needed
B1 FFFFCC	0-4mg/dL	No treatment needed
B2 FFFF00	5-14mg/dL	Phototherapy
B3 FFD300	15-19mg/dL	Phototherapy
B4 FFD700	>20mg/dL	Phototherapy /Exchange transfusion

Fig. 10. Table of Bilirubin reference card (B1-B4)

Kavya Subramanian et al. [46] proposed a non-invasive bilirubin meter. It is implemented as a smartphone. The captured image is processed and observed for the bilirubin count using the ANN algorithm. The maximum epochs are 100 for training with hidden layer 1. Best validation obtained at epoch 22. Best training performance is 0.24991 at epoch 2. It is used to find jaundice in newborn babies. A few limitations occur during image acquisition. It affects accuracy and performance. To overcome this, the high pixel mobile phone-based bilirubin meter has been developed. This method is simple and effective. It plays a vital role during the phase of phototherapy. A. Renu Deepthi et al. [47] found the detection of the bilirubin system. It emits blue light from an LED onto the infant's skin. He designed a hardware component to measure the bilirubin level. It is non-invasive with less computation time. K. Uma et al. [6] implemented homomorphic filtering to detect bilirubin levels. This method elaborates on the captured image. The detection is done based on the concentration level on the baby's skin. Performance is lower in the case of poor intensity. The amplitude effect is omitted by the homomorphic filter. The coefficient of correlation between blue intensity value and bilirubin value is calculated with and without the filter. The method is feasible. Lightson Ngashangva et al. [48] implemented a conventional method to estimate the bilirubin level. Bilirubin levels are measured by capillary, laboratory, and transcutaneous approaches.

5 Conclusion

Data mining is robust for many medical or clinical industries. It systematically facilitates health organizations using knowledge and analytics to determine low performance and excellent routines that enhance care and minimize computational cost. Computer vision techniques and machine learning methodologies are critical in analyzing data. The process consist of data acquisition, dealing, designing, and evaluating digital images. Machine learning plays a vital role in improving the accuracy and performance of computer vision techniques. It is an efficient method in computer vision. In this study, the techniques are applied in medical image analysis. The reviews were done on medical data mining, computer vision techniques, and machine learning methods. Their advantages and disadvantages are discussed. Each method has its own pros and cons based on its different datasets. The different methodologies are distinguished based on familiar accomplishments.

6 References

[1] Abbas Cheddad, Joan Condell, Kevin Curran, and Paul McKevitt, A Skin Tone Detection Algorithm for an Adaptive Approach to Steganography, Signal Processing 89 (2009) 2465–2478. https://doi.org/10.1016/j.sigpro.2009.04.022

[2] R. R. Porle, A. Chekima, F. Wong, and G. Sainarayanan, Wavelet-Based Skin Segmentation for Detecting Occluded Arms in Human Body Pose Modeling System, in: Proceedings of International Conference on Intelligent and Advanced Systems, Malaysia, 25–28 November 2007, pp. 764–769. https://doi.org/10.1109/ICIAS.2007.4658489

[3] A. M. Aibinu, A. A. Shafie, and M. J. E. Salami, Performance Analysis of ANN Based YCbCr Skin Detection Algorithm, SciVerseScienceDirect, Procedia Engineering 41 (2012) 1183–1189. https://doi.org/10.1016/j.proeng.2012.07.299

[4] Haiqiang Zuo, Heng Fan, Erik Blasch, Senior Member, IEEE, and Haibin Ling, Member, IEEE, Combining Convolutional and Recurrent NeuralNetworks for Human Skin Detection, IEEE Signal Processing Letters, Vol. 24, No. 3, March 2017. https://doi.org/10.1109/LSP.2017.2654803

[5] Endang Juliastuti, Vebi Nadhira, Yokanan Wigar Satwika, Naufal Aulia Aziz, and Naila Zahra, Risk Zone Estimation of Newborn Jaundice Basedon Skin Color Image Analysis, IEEE, 2019 6th International Conference on Instrumentation, Control, and Automation (ICA). https://doi.org/10.1109/ICA.2019.8916752
[6] Uma, J. Revathi and J. Anitha, Telemetry System for Early Detection of Hyperbilirubinemia in Neonates, Telemedicine Technologies, Copyright © 2019 Elsevier Inc. https://doi.org/10.1016/B978-0-12-816948-3.00006-4
[7] Alessandra Lumini and Loris Nanni, Fair Comparison of Skin Detection Approaches on Publicly Available Datasets, Elsevier, Expert Systems with Applications 160 (2020) 113677. https://doi.org/10.1016/j.eswa.2020.113677
[8] B. K. Harsha and Dr. G. Indumathi, Skin Detection in Images Based on Pattern Matching Algorithms - A Review, Proceedings of the Fifth International Conference on Inventive Computation Technologies (ICICT-2020) IEEE Xplore Part Number:CFP20F70-ART; ISBN:978-1-7281-4685-0.
[9] Hafiz Tayyab Mustafa, Jie Yang, and Masoumeh Zareapoor, Multi-Scale Convolutional Neural Network for Multi-Focus Image Fusion, Elsevier, Image and Vision Computing 85 (2019) 26–35. https://doi.org/10.1016/j.imavis.2019.03.001
[10] Xuecan Liang, Pengyu Hu, Liguo Zhang, Jianguo Sun, and Guisheng Yin, MCFNet: Multi-Layer Concatenation FusionNetwork for Medical Images Fusion, IEEE Sensors Journal, Vol. 19, No. 16, August 15, 2019. https://doi.org/10.1109/JSEN.2019.2913281
[11] Di Gai, Xuanjing Shen, Hang Cheng, and Haipeng Chen, Medical Image Fusion via PCNN Based on Edge Preservation and Improved Sparse Representation in NSST Domain, Received June 16, 2019, accepted June 24, 2019, date of publication June 27, 2019, date of current version July 15, 2019.
[12] Li Yin, Mingyao Zheng, Guanqiu Qi, Zhiqin Zhu, Fu Jin, and Jaesung Sim, A Novel Image Fusion Framework Based on Sparse Representation and Pulse Coupled Neural Network, IEEE Access. https://doi.org/10.1109/ACCESS.2019.2929303
[13] Kai-jian Xia, Hong-sheng Yin, and Jiang-qiang Wang, A Novel Improved Deep Convolutional Neural Network Model for Medical Image Fusion, Springer, Cluster Computing (2019) 22:S1515–S1527. https://doi.org/10.1007/s10586-018-2026-1
[14] Zhaobin Wang, Zijing Cui, and Ying Zhu B., Multi-Modal Medical Image Fusion by Laplacian Pyramid and Adaptive Sparse Representation, Elsevier, Computers in Biology and Medicine 123 (2020) 103823. https://doi.org/10.1016/j.compbiomed.2020.103823
[15] K. Padmavathi, C. S. Asha, and Maya V. Karki, A Novel Medical Image Fusion by Combining TV-L1 Decomposed Textures Based on Adaptive Weighting Scheme, Elsevier, Engineering Science and Technology, an International Journal 23 (2020) 225–239. https://doi.org/10.1016/j.jestch.2019.03.008
[16] Manjit Kaur and Dilbag Singh, Fusion of Medical Images Using Deep Belief Networks, Springer, Cluster Computing (2020) 23:1439–1453, https://doi.org/10.1007/s10586-019-02999-x
[17] Aimin Yang, Xiaolei Yang, Wenrui Wu, Huixiang Liu, and Yunxi Zhuansun, Research on Feature Extraction of Tumor Image Based on Convolutional Neural Network, IEEE Access. https://doi.org/10.1109/ACCESS.2019.2897131
[18] Dimpy Varshni, Kartik Thakral, Lucky Agarwal, Rahul Nijhawan, and Ankush Mittal, Pneumonia Detection Using CNN Based Feature Extraction, IEEE 2019. https://doi.org/10.1109/ICECCT.2019.8869364
[19] Xu Chen, Jianjun Li, Yanchao Zhang, Yu Lu, and Shaoyu Liu, Automatic Feature Extraction in X-Ray Image Based on Deep Learning Approach for Determination of Bone Age, Elsevier, Future Generation Computer Systems 110 (2020) 795–801. https://doi.org/10.1016/j.future.2019.10.032

[20] Md. Messal Monem Miah, Rafat Jamal Tazim, Fatema Tuj Johora, Md. Ibrahim Al Imran, Sanzida Sayedul Surma, Fariba Islam, Rashid Shabab, Celia Shahnaz, and Arik Subhana, Non-Invasive Bilirubin Level Quantification and Jaundice Detection by Sclera Image Processing, 2019 IEEE Global Humanitarian Technology Conference (GHTC).
[21] Mustafa Aydın, Fırat Hardala, Berkan Ural, and Serhat Karap, Neonatal Jaundice Detection System, Springer, Transactional Processing Systems, https://doi.org/10.1007/s10916-016-0523-4
[22] Yan Xu, Deep Learning in Multimodal Medical Image Analysis, Springer, HIS 2019, LNCS 11837, pp. 193–200, 2019. https://doi.org/10.1007/978-3-030-32962-4_18
[23] Afshan Latif, Aqsa Rasheed, Umer Sajid, Jameel Ahmed, Nouman Ali, Naeem Iqbal Ratyal, Bushra Zafar, Saadat Hanif Dar, Muhammad Sajid, and Tehmina Khalil, Content-Based Image Retrieval and Feature Extraction: A Comprehensive Review, Hindawi, Mathematical Problems in Engineering Volume 2019, Article ID 9658350, 21 pages. https://doi.org/10.1155/2019/9658350
[24] Md. Alok Sarkar, Md. Maniruzzaman, Shamim Ahsan, Mohiuddin Ahmad, Mohammad Ismat Kadir, and S. M. Taohidul Islam, Identification and Classification of Brain Tumor from MRI with Feature Extraction by Support Vector Machine, IEEE, 2020 International Conference for Emerging Technology (INCET). https://doi.org/10.1109/INCET49848.2020.9154157
[25] Mohamed Abdel-Basset, Weiping Ding, and Doaa El-Shahat, A Hybrid Harris Hawks's Optimization Algorithm with Simulated Annealing for Feature Selection, Springer, Artificial Intelligence Review. https://doi.org/10.1007/s10462-020-09860-3
[26] S. Shanthi and N. Rajkumar, Lung Cancer Prediction Using Stochastic Diffusion Search (SDS) Based Feature Selection and Machine Learning Methods, Springer, Neural Processing Letters. https://doi.org/10.1007/s11063-020-10192-0
[27] Mesut Togaçar, Burhan Ergen, and Zafer Cömert, Detection of Lung Cancer on Chest CT Images Using Minimum Redundancy Maximum Relevance Feature Selection Method with Convolutional Neural Networks, Elsevier, Nalecz Institute of Biocybernetics and Biomedical Engineering of the Polish Academy of Sciences. https://doi.org/10.1016/j.bbe.2019.11.004
[28] Mesut Togaçar, Zafer Cömert, and Burhan Ergen, Classification of Brain MRI Using Hyper Column Technique with Convolutional Neural Network and Feature Selection Method, Elsevier, Expert Systems With Applications 149 (2020) 113274. https://doi.org/10.1016/j.eswa.2020.113274
[29] Jiangzhang Gan, Guoqiu Wen, Hao Yu, Wei Zheng, and Cong Lei, Supervised Feature Selection by Self-Paced Learning Regression, Elsevier, Pattern Recognition Letters.
[30] Vemula Vinay Kumar, Kodali Sai Krishna, and Sarukonda Kusumavathi, Genetic Algorithm Based Feature Selection Brain Tumour Segmentation and Classification, International Journal of Intelligent Engineering and System, Vol. 12, No. 5, 2019. https://doi.org/10.22266/ijies2019.1031.21
[31] El-sayed M. El-Kenawy, (Member, IEEE), Marwa Metwally Eid, Mohamed Saber, and Abdelhameed Ibrahim, MbGWO-SFS: Modified Binary Grey Wolf Optimizer Based on Stochastic Fractal Search for Feature Selection, IEEE ACCESS. https://doi.org/10.1109/ACCESS.2020.3001151
[32] Nicolas Georges, Islem Mhiri, Islem Rekik, and the Alzheimer's Disease Neuroimaging Initiative, Identifying the Best Data-Driven Feature Selection Method for Boosting Reproducibility in Classification Tasks, Elsevier, Pattern Recognition 101 (2020) 107183. https://doi.org/10.1016/j.patcog.2019.107183
[33] Mehrdad Rostamia, Saman Forouzandehb, Kamal Berahmandc, and Mina Soltanid, Integration of Multi-Objective PSO Based Feature Selection and Node Centrality for Medical Datasets, Elsevier, Genomics 112 (2020) 4370–4384. https://doi.org/10.1016/j.ygeno.2020.07.027

[34] Warda M. Shaban, Asmaa H. Rabie, Ahmed I. Saleh, and M. A. Abo-Elsoud, A New COVID-19 Patients Detection Strategy (CPDS) Based on Hybrid Feature Selection and Enhanced KNN Classifier, Elsevier, Knowledge-Based Systems 205 (2020) 106270. https://doi.org/10.1016/j.knosys.2020.106270
[35] B. Venkataramanaiah and J. Kamala, ECG Signal Processing and KNN Classifier-Based Abnormality Detection by VH-Doctor for Remote Cardiac Healthcare Monitoring, Springer, Methodologies and Application. https://doi.org/10.1007/s00500-020-05191-1
[36] D. Benyl Renita1 and C. Seldev Christopher, Novel Real Time Content Based Medical Image Retrieval Scheme with GWO-SVM, Springer, Multimedia Tools and Applications. https://doi.org/10.1007/s11042-019-07777-w
[37] P. Indra and M. Manikandan, Multilevel Tetrolet Transform Based Breast Cancer Classifier and Diagnosis System for Healthcare Applications, Springer, Journal of Ambient Intelligence and Humanized Computing. https://doi.org/10.1007/s12652-020-01755-z
[38] Emmanuel Eragbe Sule, Development of a Skin Cancer Detection Classifier Using Artificial Neural Network (ANN), Journal of Electrical Engineering, Electronics, Control and Computer Science – JEEECCS, Vol. 7, No. 23, pages 1–4, 2021.
[39] K. R. Kruthika, Rajeswari, H. D. Maheshappa, and Alzheimer's Disease Neuroimaging Initiative, Multistage Classifier-Based Approach for Alzheimer's Disease Prediction and Retrieval, Elsevier, Informatics in Medicine Unlocked. https://doi.org/10.1016/j.imu.2018.12.003
[40] A. Shiv Gehlot, A. Anubha Gupta, and B. Ritu Gupta, SDCT-AuxNet θ: DCT Augmented Stain Deconvolutional CNN with Auxiliary Classifier for Cancer Diagnosis, Elsevier, Medical Image Analysis 61 (2020) 101661. https://doi.org/10.1016/j.media.2020.101661
[41] Gopi Kasinathan, Selvakumar Jayakumar, Amir H. Gandomi, Manikandan Ramachandran, Simon James Fong, and Rizwan Patan, Automated 3-D Lung Tumor Detection and Classification by An Active Contour Model and CNN Classifier, Elsevier, Expert Systems with Applications 134 (2019) 112–119. https://doi.org/10.1016/j.eswa.2019.05.041
[42] D. Rammurthy and P. K. Mahesh, Whale Harris Hawks Optimization Based Deep Learning Classifier for Brain Tumor Detection Using MRI Images, Elsevier, Journal of King Saud University – Computer and Information Sciences. https://doi.org/10.1016/j.jksuci.2020.08.006
[43] Yuyun Ye, Miao Tian, Qiyu Liu, and Heng-Ming Tai, Pulmonary Nodule Detection Using V-Net and High-Level Descriptor Based SVM Classifier, IEEE ACCESS. https://doi.org/10.1109/ACCESS.2020.3026168
[44] Virupakshappa and Basavaraj Amarapur, Computer-Aided Diagnosis Applied to MRI Images of Brain Tumor Using Cognition Based Modified Level Set and Optimized ANN Classifier, Springer, Multimed Tools Appl. https://doi.org/10.1007/s11042-018-6176-1
[45] Asyraf Hakimi Abu Bakar, Najmuddin Mohd Hassan, Ammar Zakaria, Khairul Anwar Abdul Halim, and Ahmad Ashraf Abdul Halim, Jaundice (Hyperbilirubinemia) Detection and Prediction System Using Color Card Technique, 2017 IEEE 13th International Colloquium on Signal Processing & its Applications (CSPA 2017). https://doi.org/10.1109/CSPA.2017.8064952
[46] Kavya Subramanian, Arvind Dhawangale, and Soumyo Mukherji, Towards Non-Invasive Detection of Neonatal Jaundice Using a Smartphone, IEEE, 2018, ISBN: 978-1-5386-8235-7/18.
[47] A. Renu Deepthi, Chanchal Singh, and J. B. Jeeva, A Device to Detect Hyperbilirubin through Non- Invasive Technique, IEEE, 2019 Innovations in Power and Advanced Computing Technologies (i-PACT), ISBN: 978-1-5386-8190-9/19. https://doi.org/10.1109/i-PACT44901.2019.8960054
[48] Lightson Ngashangva, Vinay Bachu, and Pranab Goswami, Development of New Methods for Determination of Bilirubin, Elsevier, Journal of Pharmaceutical and Biomedical Analysis. https://doi.org/10.1016/j.jpba.2018.09.034

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