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Priority Based Correlation Feature Set with Weighted Section Clustering for Melanoma Classification

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ABSTRACT
Detecting skin cancer at the right time becomes a thought-provoking problem. Diagnosis relies heavily on machine learning models. Skin cancer has become the most common kind of cancer among people of all ages. Early detection lowers mortality rates. This is achieved via a hybrid approach involving extraction of features for clustering and classification techniques. Skin lesion subclasses with the most relevant features, such as colour and texture, are allowed for categorization. In order to pick features from massive data sets that contain more unsuitable or repeated features, a methodology is devised. If not caught and treated early, melanoma, the worst form of skin cancer, can cause death. Only board-certified dermatologists can provide an accurate prediction. Due to a scarcity of qualified personnel, computer-assisted diagnosis has emerged as the method of choice. Selected feature based clustering using similar group of values and machine learning based classification technique for melanoma detection is proposed here. The system is put through its paces using a collection of dermoscopy images drawn from the normative database. In order to isolate the affected area, a feature similar based ranking clustering approach is used. Six separate color-texture feature extractors are used to pull the features from the clustered set. Disease categorization using machine learning is hindered by a lack of data and the curse of dimensionality. In this research feature dimensionality reduction model is applied that propose a Priority based Correlation Feature Set with Weighted Section Clustering (PbCFS- WSC) model. The proposed model performance is high in clustering and classification in melanoma classification when compared with the traditional models.

Keywords: Feature Selection, Feature Correlation, Feature Dimensionality Reduction, Clustering, Classification, Machine Learning, Melanoma Detection.

1. INTRODUCTION

The fields of medical image processing, recognition, and classification have developed over the past several decades to aid dermatologists [1]. Melanoma skin cancer is among the most common forms of skin cancer researches because of the severity of the disease [2]. This skin hematoma, which is on the rise across the world's population, originates in the pigmented melanosomes and is frequently mistaken for nevi or other benign lesions [3]. Therefore, non-invasive methods of immediately and automatically classifying cancerous lesions would be of great benefit to the global population.

There has been a dramatic rise in the number of cases of skin cancer, according to the World Health Organization. Melanoma and non-melanoma skin cancers are the two main categories of the disease. Worldwide, approximately two to three billion instances of non-melanoma melanoma and 17 thousand cases of melanoma cancer are reported each year. When compared to other skin cancers, melanoma has a 81% higher mortality rate. Over the past decade, deaths from melanoma have risen by an average of 3.2% annually. Early diagnosis of skin disease melanoma results in a 67% survival rate with relatively low treatment costs [4]. A low percentage of patients survive for five years after receiving treatment for advanced melanoma, despite the high costs associated with doing so. Melanoma detection in its early stages is a difficult problem that needs to be addressed [5]. The melanoma classification of the type is shown in Figure 1.

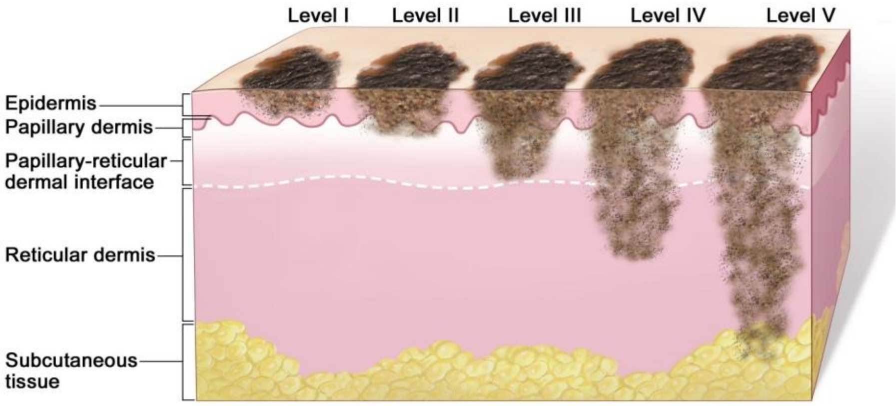

Fig 1: Melanoma Types

Dermoscopy, also referred to as skin microscopy, dermatoscopy, and epiluminescence microscopy, is a technique used by dermatologists for the diagnosis and study of skin lesions [6]. The method of dermoscopy used is completely non-invasive and is typically carried out by board-certified dermatologists [7]. Gel is placed on the skin lesion, and then a digital imaging system, such as a stereomicroscope or dermatoscope, is used to obtain magnified images for diagnosis. When viewed at a higher magnification, images of skin lesions reveal details about their colour [8], structure, and pattern that are otherwise obscured. Having this extra information is a huge help to dermatologists in determining what kind of skin lesion their patients have. Studies have shown that machine learning algorithms can detect and diagnose skin lesions just as well as human dermatologists with more accuracy rate [9]. But it is important to test how well these algorithms perform on photos that aren't often used in their domain. High variability in lesion shape, size, and location [10], low contrast among skin lesions and surrounding healthy skin, visual similarity among melanoma and non melanoma lesions, and variability in skin condition among different patients are all obstacles to the automatic detection and classification of image data using machine learning methods [11].

Features of the skin image are crucial in computer-aided detection of melanoma in order to distinguish between benign and malignant melanoma [12]. Both benign and malignant melanoma look remarkably similar in the earliest stages. These characteristics can be broken down into two broad classes: internal and external [13]. Dermascopic images can be dissected to reveal internal characteristics including blue-white veils, malignant patches of skin, and uneven streaks. Factors that can be observed by others include chronological age, cancer in the family history, skin itchiness, etc. Features should be extracted in accordance with the approach chosen for melanoma diagnosis [14]. The ABCDE traits are applied to the detection of melanomas, which stand for Asymmetry, Border, Colour, Diameter, evolution of lesion [15]. The term feature selection refers to the procedure of narrowing down a large pool of potential features to a manageable number for inclusion in a predictive model [16]. It is a common method for making feature mining and finding more productive by cutting down on the number of dimensions involved [17]. Dimensionality reduction is necessary, but care must be taken to guarantee that crucial data remains intact.

Complete research methods have been presented in the literature employing algorithms for computer vision to evaluate a skin lesion at the initial stage and to tackle the challenges outlined [18]. In the case of skin cancer data, the limitations of many machine learning approaches in terms of data processing [19], such as the need for high contrast, noise-free, and cleaned images, do not apply. In addition, skin classification is based on characteristics like colour [20], texture, and structure. Because skin lesions have a lot of inter-class uniformity and intra-class heterogeneity, the classification may produce inaccurate results with weak feature sets [21]. The conventional methods are parametric and necessitate normally distributed training data, but data on skin cancer is not systematically studied. These techniques are insufficient because each lesion has its own unique pattern.

2. LITERATURE SURVEY

The mortality rate from melanoma is the highest of all skin cancers. When melanoma spreads beyond the dermis, it becomes extremely dangerous. Because of this, depth is crucial in making a melanoma diagnosis. In this study, Satheesha, T. Y. [1] et al. presented a computerized dermoscopy system that does not require any incisions but does take into account the approximate depth of skin lesions. It is demonstrated how to reconstruct lesions in three dimensions (3D) by using the approximate depth found in routine dermoscopic images. It is possible to extract depth & 3-D shape features from the reconstructed model. It is possible to extract regular colour, texture, & 2-D shape features in furthermore to 3-D features. To get reliable outcomes, feature extraction is indispensable. It is anticipated that the proposed system will also be useful in the diagnosis of basal carcinoma, blue nevus, dermatofibroma, haemangioma, seborrheic keratosis, and normal mole lesions in addition to melanoma and in-situ melanoma.

Pereira et al. [2] provided a step forward in the use of deep learning (DL) techniques to detect melanomas. Melanoma is the deadliest form of skin cancer, and this area of study aims to find non-invasive ways to help with detection and classification. The proposed method goes beyond the commonly used color and texture features of image data by taking advantage of both 3D and 2D character traits of a skin lesion surface. The use of a Multiple Instance Learning (MIL) and a DL, two competing classification methods, combined with an uncertainty-aware decision function, is explored. In contrast to MIL's 3D feature extraction, selection, and classification at two distinct learning instances, DL relies on RGB data to perform classification.

When caught early, melanoma can be treated successfully, and the survival rate significantly improves. The recognition of melanoma from dermoscopy images using learning-based methods shows great promise. Due to its rarity, melanoma has resulted in a highly skewed proportion of benign to malignant samples in database files of skin lesions. As a result, classification models are heavily skewed toward the majority class due to the imbalance. .Ztürket al.[3] proposed a deep clustering method that uses a latent-space embedding of dermoscopy images to solve this problem. Image embeddings from a convolutional neural network's backbone are used in conjunction with such a novel center-oriented margin-free triplet loss (COM-Triplet) to achieve clustering. The proposed method is more robust to class imbalance because it focuses on creating maximally-separated cluster hubs rather than minimizing classification error. Moreover, the author proposed implementing COM-Triplet using pseudo-labels produced by the Gaussian mixture model, thus eliminating the need for labelled data. Extensive experiments demonstrate that in both supervised and unsupervised settings, deep clustering to COM-Triplet loss outperforms clustering with triplet loss and competing classifiers.

Even though the number of young people affected is rising, survival rates improve dramatically when the disease is detected early. When it comes to diagnosing melanoma, both the time and money spent by doctors are extremely high. Here, Khan et al. [4] proposed a smart system that employs cutting-edge image processing methods to spot melanoma and differentiate it from a nevus. The acquired images have their skin lesion noise reduced using a Gaussian filter, and then the lesion itself is segmented using an enhanced version of the K-means clustering algorithm. The extraction of chromatic and textural features from the lesion produces a unique hybrid superfeature vector. Melanoma and nevi are separated in the categorization of skin cancer using a support vector machine. The purpose of this study is to evaluate the performance of the suggested segmentation approach, identify the best features to extract, and evaluate the classification results against those obtained using other methods. The author put the proposed methodology to the test on the DERMIS dataset, which contains 397 images of skin cancers. The results of the proposed methodology are very encouraging, with an accuracy of 96%.

Viruses, bacteria, fungi, and chemical imbalances are common causes of skin diseases. The key to stopping the spread of these diseases is prompt analysis and identification. The lack of experience in primary health centers makes disease control especially challenging in rural as well as resource-poor settings. Therefore, it is important to provide innovative and self-helping measures for accurate skin disease diagnosis. Mobile app use has the potential to deliver low-cost, low-effort, high-yield answers to the challenges of early detection and treatment. To use a Mahalanobis distance measure, Gupta et al. [5] analyzed and classes skin diseases based on their visual images, applying the Gaussian mixture model (GMM). Mobile device constraints have led to the GMM's adoption in place of the more powerful convolution neural network.

Computer vision applications rely heavily on the ability to detect and remove distracting features from images. As such, denoising, dehazing, and deraining have all been the subject of extensive research in both classical model-based techniques and cutting-edge deep learning strategies. Despite its importance and potential, however, removing hair from dermoscopy images really hasn't received enough attention. Meanwhile, most hair removal algorithms continue to use outdated, manual methods, while only a few experiments use modern, data-driven approaches. In dermoscopy applications, it is preferred that hair be shaved off because it can obscure the view of lesions and other abnormalities. Hair removal is difficult because of the complexity and variability of hair itself. Kim et al. [6] proposed an unsupervised method for hair removal & test it on a dataset of actual melanoma cases. The proposed method uses generative adversarial learning to remove hair from dermoscopic images. This is accomplished by causing a recreated distribution of pictures with hair to represent a hairless distribution.

While there has been progress in automatically recognizing skin lesions using deep learning techniques, the method isn't without its drawbacks, including insufficient training data, a convoluted network architecture, and high computational costs. Malicious melanoma & benign melanocytic nevi skin lesion classification using convolutional SNNs to unmonitored spike-timing-dependent plasticity (STDP) user training is presented in this paper by Zhou et al. [7] to demonstrate the power-efficiency, biological plausibility, and good image identification effectiveness of spiking neural networks (SNNs).

Yang et al. [8] proposed a new melanoma classification method using convolutional neural networks for dermoscopy images. As a first step, the author presented the region mean pooling technique for concentrating feature extraction in a specific area. The fragmented lesion region is then used to direct RAPooling's classification. This complete classification framework is then designed. The area underneath the ROC curve is then used to optimise a linear classifier called RankOpt, and the resulting classification is obtained. In addition to improving classification performance for an unbalanced dermoscopy image dataset via optimization of RankOpt, the proposed method also incorporates segmentation data into the task.

Many people all over the world are at risk for developing melanoma, a particularly aggressive form of skin cancer. Dermatologists may make mistakes when attempting to diagnose melanoma visually. Therefore, the use of AI-enabled image processing devices can aid dermatologists in their diagnostic and treatment processes. However, distinguishing melanomas from benign tumours is challenging due to the wide range of features shared by these lesions and also the existence of noises and artefacts in the images. Ichim et al. [9] proposed a novel intelligent system in this research, one that makes use of multiple neural networks interconnected at two levels of specificity. There are five different classifiers used on the first level: a perceptron trained with colour local binary patterns, a perceptron trained with colour histograms of oriented gradients, a feedforward neural network trained with the ABCD rule, a ResNet, and an AlexNet. They take into account the texture, shape, colour, size, as well as convolutional pixel connections of melanomas in their experimental selection.

3. PROPOSED MODEL

One of the three most lethal forms of cancer produced by DNA damage is skin cancer. This DNA damage causes cells to multiply rapidly and out of control, and it is becoming increasingly common in modern times. Some studies have been conducted on the use of computers to determine whether or not a skin lesion is cancerous [22]. The examination of these images, however, is complicated by a number of factors, including light reflections off the skin's surface, variations in color lighting, and differences in the form and size of the lesions [23]. Therefore, early-stage pathologists can benefit greatly from evidence-based automatic detection of skin cancer.

As soon as the region of interest has been cut off, any remaining aspects of the lesion that are relevant to the problem at hand can be extracted. Using the ABCDE rule, seven geometric features and one colour feature are retrieved from the lesion image. Each of the five requirements that make up ABCDE can be broken down into one of two categories: the display of shape qualities (A, B, and D) and chromatic information (C,E). Some analysis of attributes from the binary segmented lesion is required before the shape features can be computed. Image moments are used to determine the best fitting ellipse in the lesion image and extract its area [24], centroid, perimeter, radius, smoothness, orientation angle, and primary axes lengths. Here, principal axes identify the major axis and minor axis of the best fitting ellipse for the lesion [25], and orientation specifies the angle between these two axes and the x-axis of the coordinate system [26]. Asymmetry is a crucial metric for assessing melanoma. It is necessary to align the segmented image with the image coordinate system in order to find the asymmetry feature. The image is rotated by its orientation angle such that its major axis lines up with the x-axis, and its centroid is then translated to the coordinate system's origin.

The overall melanoma mortality rate is increasing and is one of the few cancer mortality rates that is not decreasing. The ABCDE descriptors are the most widely used criteria for diagnosing melanoma, and these approaches have traditionally placed an emphasis on spotting evolving lesions, identifying outlier lesions, and identifying characteristic melanoma features for accurate predictions. For severe lesions, where the borders of the lesions are outside of the dermoscopy image or there is a seamless transition between both the lesions and the healthy skin, extra difficulties with application of the ABCDE descriptors occur. Therefore, it is necessary to discover alternative diagnostic features that accurately characterize skin lesions.

Increasing efforts are being made to create automated tools to aid dermatologists in the detection of melanoma at an early stage. It is composed of a few primary phases, including picture segmentation, feature extraction and selection, and lesion classification. Many new perspectives on these issues have been suggested in recent years. New mathematical border descriptors for images of pigmented skin lesions were calculated, such as the lesion slope and the lesion slope regularity.Color texture, global/dynamic thresholding, color clustering, wavelet analysis, Markov tree features, and so on are all examples.

To choose features most suited for melanoma recognition, a strategy based on the application of feature correlations, and a rapid correlation-based filter is applied. The chosen descriptors serve as input attributes to the classifier system that is ultimately responsible for melanoma recognition. A computational approach is proposed that uses a few steps of processing to identify melanoma from colourimages of skin lesions. The initial step is to use dermoscopy to obtain a raw RGB image of the affected skin. The image's numerical features, which will serve as input attributes to the classifier system, are generated. In the feature selection process, the capacity of these traits to distinguish between classes is evaluated. Selected features are used as input attributes to the classification algorithm, which is ultimately responsible for distinguishing between non-melanoma and melanoma instances. In this research feature dimensionality reduction model is applied that propose a Priority based Correlation Feature Set with Weighted Section Clustering (PbCFS- WSC) model. The process is explained in different steps clearly.

Input: Melanoma Feature Dataset {MFDset}

Output: Priority based Correlation Feature Set {PFset}

Step-1: The features are extracted from the denoised melanoma images dataset and these features are processed for accurate melanoma classification. The features are processed by calculating the mean and standard deviation as

$$Fproc[MFDset[N]] = \sum_{i=1}^{N} \lambda\left(getattr(i)\right) + \frac{mean(getattr(i, i+1))}{len(MFDset)} + std(maxattr(i, i+1))$$

Here λ is the model for retrieving the total records attributes from the dataset considered .

Step-2: The features processed are considered and the feature vectors are generated based on the minimum and maximum values among the extracted features. The max feature vector and min feature vector are generated and the process of vector generation is performed as

$$\mathrm{FeatSet}\left(\mathrm{Fproc}(\mathrm{N})\right) = \max(\lambda) + \left(\mathrm{Max}\left(\mathrm{getattr}(\mathrm{i}+1, \mathrm{i})\right) + \frac{\mathrm{Max}\left(\mathrm{getattr}(\mathrm{i}+1, \mathrm{i})\right)}{\mathrm{len}(\mathrm{Fproc})}\right) + \left[\frac{\max(mean(i+1) - \min(mean(i))}{\omega}\right]$$

Here ω represents the features set count extracted from the dataset and mean model calculates the features attributes mean and standard deviation using std model.

Step-3: When feature selection is performed, correlation is an effective method for considering those variables that are most strongly linked to the intended outcome. It's crucial that the variables connect to the endpoint but stay independent from one another. If two variables are highly linked, users can extrapolate information about the first variable from information about the second. The calculation of the correlation between features proceeds as

$$\mathrm{FeatCorrSet}(\mathrm{Featset}(\mathrm{N})) = \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{corr}\left(\max\left(\mathrm{FeatSet}(\mathrm{i}, \mathrm{i}+1)\right)\right) - \mathrm{corr}(\min\left(\mathrm{FeatSet}(\mathrm{i}, \mathrm{i}+1)\right)}{\sum_{\mathrm{i}=1}^{\mathrm{N}} \min(mean(i)) + \omega}$$

The corr model is used to identify the correlation among the features extracted based on the dependency of the features on other features.

Step-4: The priority allocation is performed on the features that represent the sequence of features selected in training the model. The feature priority allocation is performed based on the relevancy of the values to the optimal solution that is performed as

$$PFset(N) = \prod_{i=1}^{N} \frac{H(\max\left(FeatCorrSet(i+1, i)\right))}{count(Feat\ Set(N))} + \max_{i \to N}\left(\max(Corr(\lambda + i + 1)) + \frac{Max(FeatSet(i))}{\omega}\right)$$

Step-5: The goal of clustering in machine learning is to identify collections of features that share similarities among themselves but are distinct from features in other collections. Clustering is a technique used in feature analytics to categorize large feature sets into smaller feature vectors with more manageable chunks based on their shared characteristics. The feature clustering is performed as

$$PCFset(PFset(r)) = \bigcup_{i=1}^{N} \frac{simm(PFset(i+1, i))}{\max(simm\left(PFset(N)\right))} + \frac{\delta(mincorr(i+1, i))}{\lambda}$$

Here δ is the mode for removing the high correlted features from the extracted feature set for training the model.

Step-6: The weight allocation is performed to the clusters based on the dependencies of the feature sets on other feature sets. The weight allocated features are used for classification for accurate detection of melanoma. The process of Weighted Section Clustering is performed as

$$WClusterSet[N] = \sum_{i=1}^{N} \max(simm\left(PCFset(i, i+1)\right) + \sum_{i=1}^{N} \max_{0 \le i \le N} \frac{\min(simm(PCFset(i, i+1))}{\omega}$$

4. RESULTS

The most lethal kind of skin cancer is melanoma. For decades, its growth has been nothing short of meteoric. The survival percentage is extremely high if caught and treated early. Automated melanoma detection using dermoscopy images has been a popular topic of study for the past few decades as a means of avoiding the need

for invasive biopsy. This research uses the ABCDE rule to propose novel, distinct, and efficient features for identifying melanomas in dermoscopy pictures based on shape, size, and colour properties. In order to derive a mixture of essential features that correlate to different properties of the lesion, the focus of this research is on feature selection. Furthermore, the relationship between particular characteristics and clinical criteria is demonstrated, as is the optimum number of features for a given classifier. The research findings apply to a wide range of classification problems involving high-dimensional feature spaces and are not limited to those in the medical field.
The dataset contains 25331 dermoscopic images of skin lesions together with their associated segmentation and metadata. The information has been arbitrarily divided into a set for training and validation (75%) and a set for testing (25%). Estimating the right class of each dermoscopy images image in the test set is the objective of this research. The dermoscopy image dataset is considered from the link https://www.kaggle.com/competitions/ima205-challenge-2022/data. In this research feature dimensionality reduction model is applied that propose a Priority based Correlation Feature Set with Weighted Section Clustering (PbCFS- WSC) model. The proposed model is compared with the traditional multi-tree genetic programming (MTGP) model.
Feature selection is the process of narrowing down the data used in the model by keeping just the most pertinent information and discarding any irrelevant or extraneous details. It is when a machine learning model makes feature selections on its own, taking into account the nature of the problem of melanoma detection using the selected features. The Figure 2 shows the Feature Selection Time Levels of the proposed and traditional models.

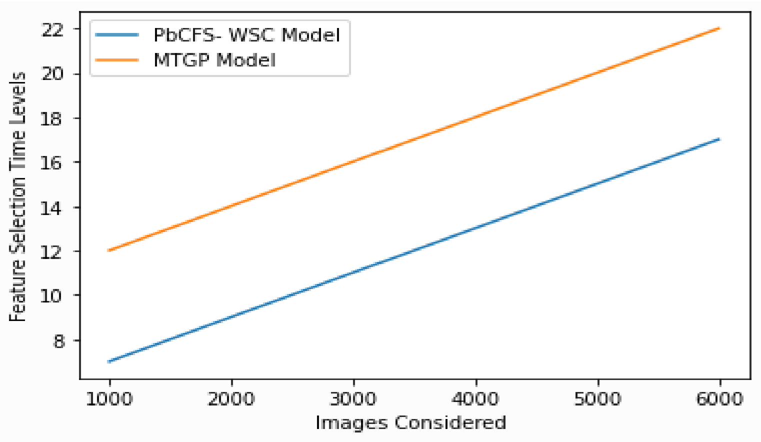

Fig 2: Feature Selection Time Levels

This correlation evaluation formula is coupled with a suitable correlation measure in the algorithm. Experiments were conducted using both synthetic and natural datasets to assess Correlation based Feature Selection. The linear link between two or more variables can be measured using the concept of correlation. It is possible to make inferences about one variable based on another through the use of correlation. The relevant features, according to the reasoning behind utilizing correlation for feature selection, should have a high degree of correlation with the target. The Feature Correlation Calculation Accuracy Levels of the proposed and traditional models are shown in Figure 3.

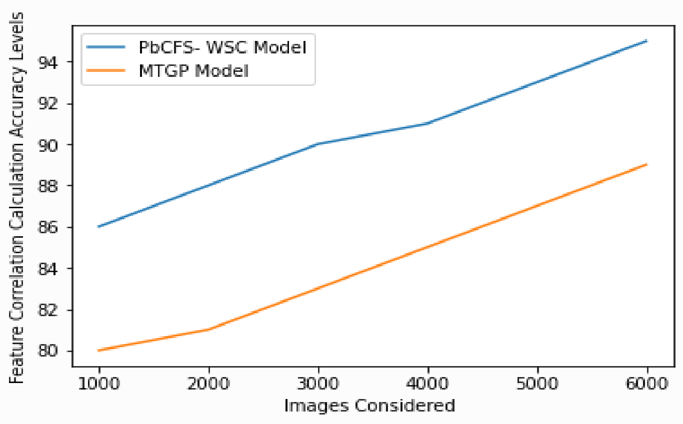

Fig 3: Feature Correlation Calculation Accuracy Levels

Algorithms that pick the most useful components of an input collection of features are called feature selection algorithms. By multiplying each feature by a weight value based on its discriminatory power, feature weighting helps to determine which features are most useful for identifying different types of patterns. Reducing the dimensionality of data and increasing classification accuracy are two common goals, and selection of features and feature weighting were two tried and true methods for doing both. Only data with redundant and unrelated features should use feature selection, whereas data with variable relevance should use feature weighting. The Figure 4 shows the Feature Weight Allocation Time Levels of the proposed and existing models.

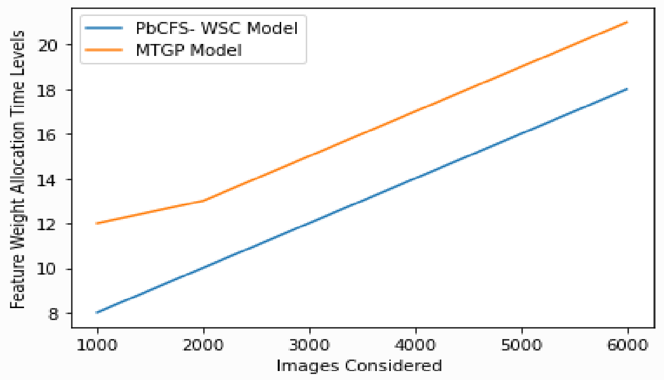

Fig 4: Feature Weight Allocation Time Levels

When trying to organize data into meaningful clusters, cluster analysis is the method used to identify and collect items that belong together. It is an algorithm for unlabeled data in machine learning. A cluster is a collection of related feature items that have some common characteristics. The Feature Clustering Accuracy Levels of the existing and proposed models are shown in Figure 5.

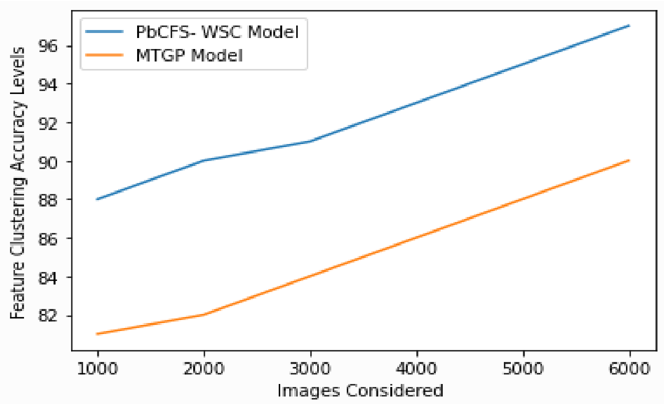

Fig 5: Feature Clustering Accuracy Levels

The Feature Weighted Section Clustering is the process of grouping features of similar king with a unique weight for training the model. The sequence represents the relation of features to train. The Feature Weighted Section Clustering Time Levels of the proposed and existing models are shown in Figure 6.

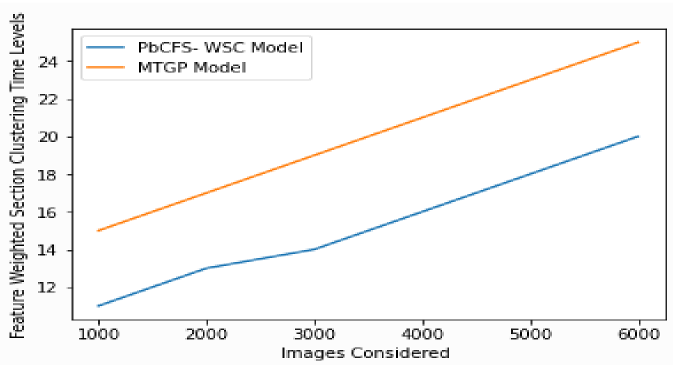

Fig 6: Feature Weighted Section Clustering Time Levels

High compactness is characterized by low mean within cluster variance. Several indices, such as the cluster wise inside average/median lengths between feature sets, are based on distance measurements to determine the compactness of clusters. Rearranging the rows of the confusion matrix such that the mean of the vertical values is minimized can be used to compute accuracy for clustering. The Feature Weighted Section Clustering results in the final weight allocation to the feature clusters. The Feature Weighted Section Clustering Accuracy Levels of the existing and proposed models are shown in Figure 7.

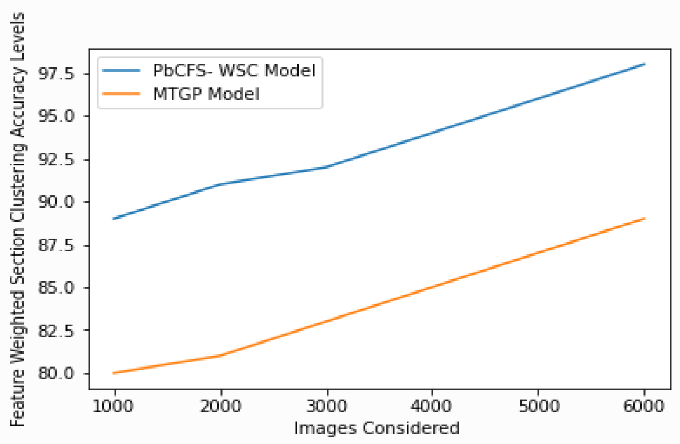

Fig 7: Feature Weighted Section Clustering Accuracy Levels

5. CONCLUSION

This research introduces an innovative approach to melanoma diagnosis using dermoscopy images features. To differentiate melanomas from other skin lesions, colour photographs of the lesions are considered. Images' diagnostic characteristics utilised for final information processing are generated using many features. As a kind of cancer, melanoma is among the most dangerous, but if caught early, it is curable. Automating the detection of skin cancer at an early stage requires a system that can analyse digital epiluminescence microscopic pictures. The segmentation process is followed by the calculation of most relevant features with less correlation characteristics that indicate form and radiometric properties. This paper considers Priority based Correlation Feature Set with Weighted Section Clustering model to assess the features' quality. The outcomes demonstrate that the feature set may be decreased with almost no loss of information when using any of the selection methods. Many of the retrieved features used in these programmes are either pointless or lack substantial data. The core application must work harder to perform its primary function if these extra features are not removed. In the proposed model, a subset is chosen as the solution to optimise the value of an evaluation metric. This research presents a novel method for feature selection to train the model for differentiating between malignant and benign dermoscopy images. The proposed model achieves 97% accuracy in weighted feature set generation used to perform training the model. In future, dimensionality reduction can be applied on the generated feature set to reduce the features to reduce the training time complexity and also to enhance the system performance with less false predictions.

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