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RESEARCH ARTICLE

Computer aided decision making to use optimum water in safflower growing

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ABSTRACT

In plants, it is one of the important factors to provide ecological factors for productivity. Plants perceive the effects of environmental factors outside as stress and create appropriate physiological responses in their metabolism. Water stress is a type of abiotic stress and is one of the important factors affecting the growth and development of plants. Irrigation water management is very important for sustainable use of water resources. Therefore, support tools are becoming increasingly important in deciding irrigation. With the developments the technology, computerized support applications are usually used in agricultural areas. In the study, it is aimed to determine the effects of irrigation applications performed in different periods on yield quality and spectral reflections of safflower plant and to create applicable irrigation programs in safflower cultivation. From the reflections detained from safflower leaves by using spectroradiometer device, the determination of safflower plant according to water ratio different situations is done. Reflections are taken as three groups where the plants are grown at wavelengths of 325 nm to 1075 nm. Water due diligence related with safflower is consist of two stages. The first stage is the provision of the feature vector, the second stage is the classification of the feature vector related to data. As classification methods, support vector machine, k-nearest neighbor and decision tree are used. In comparison of three groups, the average value of the performance is high. As a result, considering the fallowed method and the procedure used, it is evaluated that such studies can be used in agriculture and cultivation.

Keywords: Irrigation; Water Stress; Machine Learning Algorithms; Spectroradiometer; Classification

INTRODUCTION

Safflower is one of the oilseed plants of composite family and can be planted in summer and winter. As the variety of this plant develops, the oil content is increased from 25-27% to 46-47%. It is seen that it has reached an important level for humanity and the production opportunities of these plant are increasing every passing day and increase in productivity are provided with the discovery of the use of vegetable oils in the energy sector as well as the food industry. Safflower is more resistant to drought, cold and salinity than the other oil seed plants. As the summer and winter types are developed and can be grown in different climates and at different times, it becomes an excellent alternative plant in the production of biodiesel and in the production of vegetable oil and fodder deficit in dry and irrigated agricultural areas. (Eryılmaz et al 2014) As in all kinds of plants, productivity is one of the most important factors. The first factor affects the productivity is the efficient usage of water. It can be mentioned that there are two important stage of irrigation water management. The first is the bringing of the water source to the field and application, the other is management of the system. In the operation of the irrigation system, various methods can be mentioned in real time determination of when and how much water is required. The main basis of this purpose is monitoring the sail water content, observing the symptoms occurring in the plants and measuring the climate parameters (Köksal and Yilmaz 2011). In the water irrigation method, the main approach is not to use excess water when the water source is adequate and to obtain the highest efficiency with the existing water when the water source is insufficient. The water's sufficiency and insufficiency can cause redundant water usage and plant stress (Camoglu et al. 2011). The plant stress damages anatomy, morphology, physiology and chemical od the plant. This situation can be observed from the leaves of plant. Plants absorb, reflect, emit or distribute radiation from any source in accordance with radiation theory. These processes usually take place in plant leaves. Therefore,

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measurements can be made with spectoradiometer devices (Basayigit et al. 2008). The data obtained with the help of spectral feature differences can be evaluated and stored in a computerized environment. There are important relationships between the different wavelengths of the electromagnetic spectrum and the physiological state of the plants and plants can be distinguished from each other using these wavelengths (Sarı et al. 2007). The spectroscopy approach has many advantages such as high efficiency, simple operation, low cost, good reproducibility, rapid and nondestructive measurement (Wu et al. 2008). The use of automated methods in plant identification is of vital importance in protecting products (Rumpf et al. 2010). These transactions can be done using machine learning methods. Information can be obtained from spectral reflections of plants using SVM, PCA, KNN, ANN, FL methods (Kamlapurkar. 2016). Similarly, KNN, DT methods can be used (Mucherino et al. 2009). When studies related to the subject are examined; Xie et al. categorize the tomatoes healthy and diseased in the range of 380 - 1023 nm using the KNN method (Xie et al. 2017). Rahmani et al. compared plant leaves by using KNN, NB and DT classification methods (Rahmani, et al. 2015). Babatunde et al. examined the images of plant leaves using Cellular Neural Networks (CNN) (Babatunde et al. 2014) In another study, Ihuoma and Madramootoo conducted a comprehensive study of recent developments in product water stress perception (Ihuoma and Madramootoo 2017). Maimaitiyiming et al. had done a study on the water stress of different irrigation practices in vineyard trial areas (Maimaitiyiming et al. 2017). Wang and Jin aimed to obtain leaf-scale transpiration through hyperspectral reflection using Partial Least Squares Regression analysis (Wang and Jin 2015). Wang et al. tried to estimate water stress from spectral reflections by remote sensing techniques in wheat (Wang et al. 2015). Ngo et al. made a study on the variability and similarity of reflection of Chinese cabbage and cabbage plant leaves' measurement of reverberation (Ngo et al. 2015). In their study, Li et al. studied 14 species of tea plants for the rapid determination of tea polyphenols by using infrared spectroscopy using the potential data mining technique (Li at all 2015). Meng et al. carried studied on the development of agricultural equipment systems based on machine vision and fuzzy control (Meng et al. 2015). Zheng et al. showed that the electrical properties of corn leaves can be used to evaluate water stress effectively (Zheng et al. 2015). Nigon et al. carried out a study on nitrogen stress using spectral data on two potato varieties (Nigon et al. 2015). Ngo et al. made a study on determining the number of samples for optical reflection measurement in cabbage leaves (Ngo et al. 2015). Zhang et al. conducted a study on the estimation of apple sugar content based on the spectral properties of apple tree leaf at different phenological stages (Zhang et al. 2015). Lin et al. In their work, they combined computer vision and near-infrared to realize a rapid and nondestructive analysis of safflower (Lin et al. 2020). Suleiman tried to detect safflower diseases using Clips and Delphi expert system languages (Suleiman 2019). Zou et al. conducted a study on the rapid identification of adulterated safflower seed oil using hyperspectral spectroscopy (Zou et al. 2021).

In this study, their performance are compared by forming three groups to be used for irrigation water management in safflower. With the estab-lished field experiment, different water stress and plant development levels are formed and reflection values are taken from the leaves of safflower plants where irrigation water is applied at three different levels. Data obtained from spectral reflec-tions are measured as suggested in previous studies. In the study, the dataset was created primarily as the original values and the synthetic values. After, attributes are determined and then the comparison methods are compared using Suppert Vector Machine (SVM), K Nearest Neighbor (KNN) and Decission Tree (DT). Briefly, the main objective of this study is to determine the stress level of the amount of water used in safflower cultivation by machine learning methods.

MATERIALS AND METHODS

Data acquisition and the device used

The records used in the study are obtained by spectroradiometer device. The spectroradiometer operates as a multi-spectrometric optic system that records the reflected radiation from the target object after optically and electronically processing it. The spectroradiometer can be used both in open field and indoor laboratory. Solar radiation source is used when used outdoors and lamps with suitable features are used in laboratory (Keskin 2007). The data used in the study are carried out at GAPTAEM Talat Demirören Research Station and Koruklu Central Enterprise, located between 360 47 'and 390 15' east longitudes and 360 40 'and 37o 41' north latitudes in the Harran Plain of Şanlıurfa. Soil characteristics of the region are alluvial main material, flat and close to the slope, deep soils (Dinç et al., 1988).

The climate is influenced by the Mediterranean climate, which is hot and dry in summers and mild in winters. The rainfall increases from south to north and west to east. Table 1 shows the physical and climatic values of the study area.

For the data set, 60 samples were taken from a total of three groups with 5 repetitions between 1 nm interval and 325-1075 nm wavelengths. Recordings were taken separately as data gathering distance is 50m and 100m and lenses are 1^0 and 10^0. The visual of the safflower plant

Table 1: The physical and climatic values of the study area

Air pressure (mb)	Temperature (°C)	Moisture (%)	Wind Direction Angle	Wind direction	Wind speed (km/h)	Monthly Precipitation (mm)	Annual Precipitation (mm)	10 cm Deep Soil Temperature (°C)	Soil Moisture at 15 cm Depth (cb)	Soil Moisture at 55 cm Depth (cb)	Leaf Wetness Index
1016.5	19.9	34	260	Batı	9.7	8.89	77.22	15	33	113	0

and spectroradiometer device is given in Fig. 1. The data set used in the study was formed from the information obtained by using lenses 1^0 and 50m distance.

Data grouping and processing

Reflection values of the specimens of safflower leaves are obtained by spectroradiometer. The received records consist of W1, W2 and W3 data sets. For each data set, recordings are created in three separate periods as bolting, pre-flowering and seed tying. No water is applied to the aspirate in the W1 dataset. Sufficient water is applied in the W2 dataset and half of the W2 status is applied in the W3 dataset. Table 2 summarizes the water status in the plant. Since the study is carried out in terms of productivity, the reflection values obtained during the seed binding period are used in our application.

Each of the W1, W2 and W3 data sets consists of 751x20 size markers and a total of 751x60 spectroradiometer data are available. Later on, 20 synthetic data were created for each of the W1, W2 and W3 datasets, and a total of 751x60 synthetic data was created. The original data and the spectral reflections of the three groups of synthetic data are given In Fig. 2. It was observed that the synthetic data created overlapped with the original data.

Recommended system for classification determination

The detection flow chart proposed in this study is given in Fig. 3. First, the dataset was obtained in three separate cases and converted into a suitable format to be studied in computer environment. In the first of these three separate cases, the original data was processed; in the second case, synthetic data was created as much as the original data and processed; and in the third, only the synthetic data generated was processed. The attributes of the datasets created in these three separate cases were determined and classified. At the stage of classification, the training and test data of the data were divided into 80% training and 20% testing, as is often the case in field reviews. The data were recorded by collating and replicating 10 times and averaging. Another separation process was performed by doing cross validation and changing random training and test cluster patterns. All the patterns were used in both training and testing because of cross validation application. Thus, the memorization of the program's training and test values were prevented. Output values of three conditions (W1, W2 and W3) were detected by using SVM, KNN and DT as classification methods.

Table 2: Summarizes the water status in the safflower plant

Safflower Group	Periods		
	Stem Elongation	Before Flowering	Seed Formation
W1	No Water	No Water	No Water
W2	Full Water	Full Water	Full Water
W3	Half of the W2 status	Half of the W2 status	Half of the W2 status

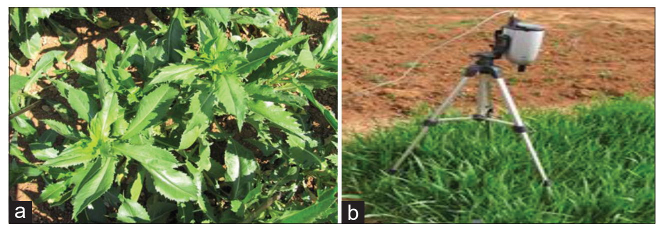

Fig 1. Safflower plant (a) and spectroradiometer device (b).

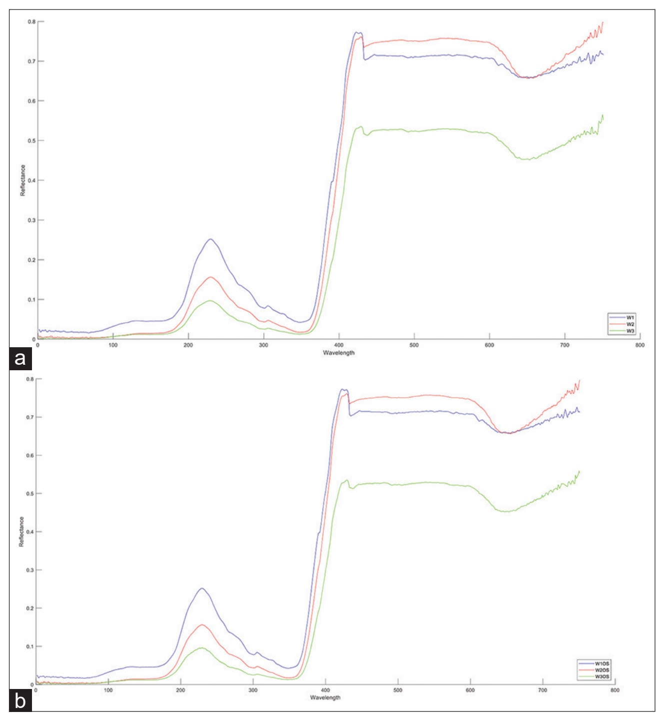

Fig 2. Spectral reflections of the raw data (a) and synthetic data (b) of the three groups.

Methods used in classification

All experiments in the study are done in CPU (Intel Core i5-7400) Windows 10 Pro with 3.00GHz, 8GB RAM and 1TB hard disk. Operating system and the software section, MATLAB R2018a is used, and machine learning (ML) methods are applied. Arithmetic mean, standard deviation, minimum, maximum, absolute value of the maximum and minimum difference, skewness, kurtosis and variance are used as statistical methods. Synthetic minority oversampling technique was used as the synthetic data generation method. In this technique, each sample of the minority class is taken, and synthetic samples are created by examining any or all of the neighbors of the sample taken randomly. This way, examples belonging to the minority class are increased and the data is over-sampled (Chawla et al. 2002). ML methods, in which the highest scores are obtained, SVM, KNN and DT are used as classification.

RESULTS AND DISCUSSION

In this study, it was aimed to classify the irrigation topics related to the records of three data sets according to their spectral reflections and to evaluate the potential of these reflections to differentiate between irrigation subjects and to achieve this objective, ML was achieved. The distribution of the attributes attribute1 - attribute2 of the original data set belonging to the safflower and the distribution of the attributes attribute1 - attribute2 obtained by using statistical values are given in Fig. 4.

Likewise, the distribution of the attributes attribute1-attribute2 of the synthetic data generated belonging to safflower and the distribution of the attributes attribute1-attribute2 obtained by using statistical values are given in Fig. 5. Blue ones represent W1, red ones represent W2, and yellow ones represent W3.

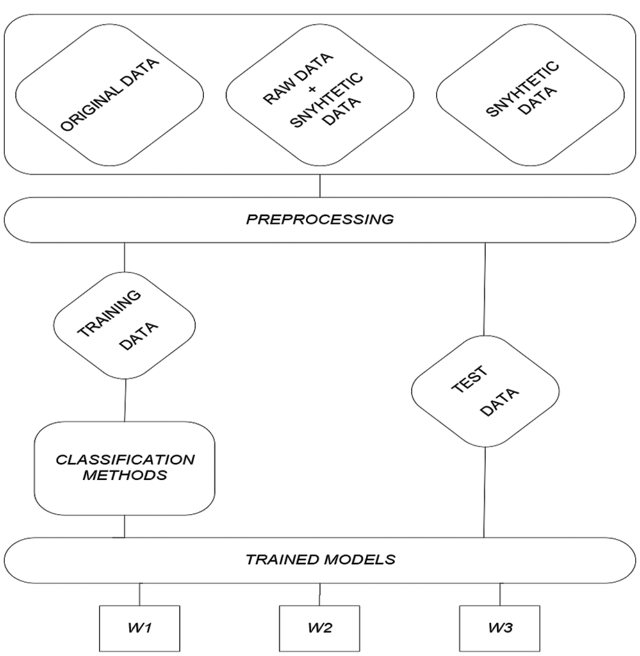

Fig 3. Flow chart of the study.

Attribute vectors of each record were obtained by using statistical data and included in the classification process. The average values of the statistical values of safflower are given in Table 3. In both cases, it is observable that the distribution of the attributes created with the statistical values of the dataset is more distinctive.

SVM, KNN and DT were used as classification method. First, the datasets were directly evaluated and then, the statistical values of the datasets were calculated and classified. Then, in order to increase the dataset, synthetic data was created and in the same way, the dataset was classified directly and by calculating the statistical values. In the classification process, when the data was separated as training and testing, it was determined as 10-fold cross validation and 80% training - 20% testing.

To assess the success of detecting the distinction of irrigation issues, Eq. 1-4, Classification Accuracy (CA), True Rate (TR), F-Score and G_Mean was used.

$$CA = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$TR = \frac{\frac{T_{c1}}{c_1} + \frac{T_{c2}}{c_2} + \frac{T_{c3}}{c_3} + \ldots + \frac{T_{cn}}{cn}}{n} = \frac{\sum_1^n \frac{T_{Cn}}{C_n}}{n} \tag{2}$$

$$\text{F-Score} = 2 * \frac{\left(\frac{TP}{FP + TN}\right) * \left(\frac{TP}{TP + FN}\right)}{\left(\frac{TP}{FP + TN}\right) + \left(\frac{TP}{TP + FN}\right)} \tag{3}$$

$$G\_Mean = \sqrt{\left(\frac{TP}{TP + FN}\right) + \left(\frac{TN}{FP + TN}\right)} \tag{4}$$

If we define class labels of the binary (two class) prediction problem as positive and negative, classifier has the following four possible outcomes: True positive (TP): The number of positive samples correctly predicted. True negative (TN): The number of negative samples correctly predicted. False positive (FP): The number of positive samples incorrectly predicted. False negative (FN): The number of negative samples incorrectly predicted. The success rates obtained for the three cases when the dataset converted into a suitable format for classification was processed directly are given in Table 4.

As another alternative, attribute inferences were obtained by using statistical values and classified. Achievement results are given in Table 5.

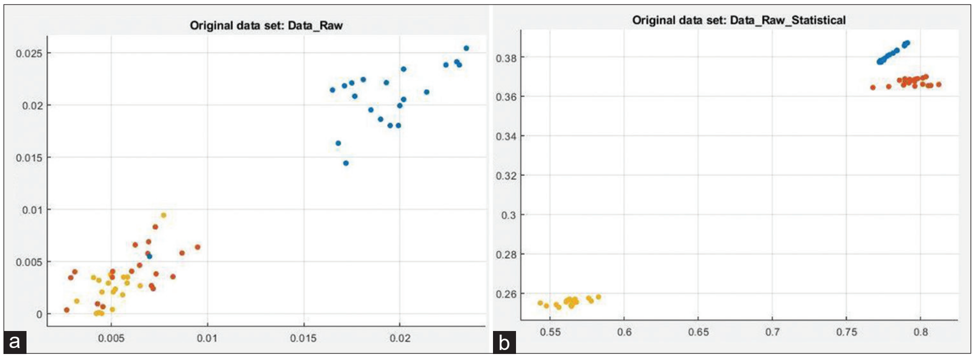

Fig 4. Distribution of attributes of raw data (a) and statistical data (b) (ex. attribute1 - attribute2).

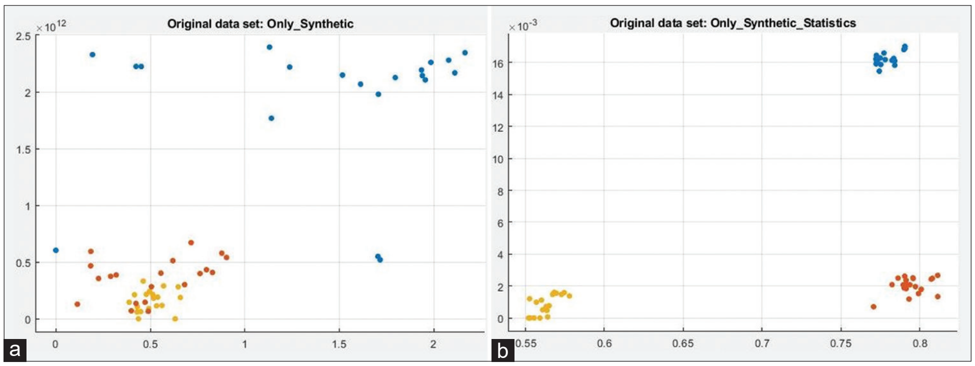

Fig 5. Distribution of attributes of synthetic data (a) and statistical data (b) (ex. attribute1 - attribute2).

Table 3: Average of the statistical values of each group

	Max	Min	Imax-minI	Mean	Std	Kurtosis	Skewnes	Var
Raw Data								
W1	0,7793	0,0161	0,7632	0,3809	0,3127	1,1124	0,0234	0,0978
W2	0,7945	0,0017	0,7928	0,3671	0,3387	1,0883	0,0901	0,1147
W3	0,5636	0,0007	0,5629	0,2554	0,2391	1,0845	0,1067	0,0572
Raw Data + Synthetic Data								
W1	0,7793	0,0162	0,7631	0,3809	0,3126	1,1124	0,0234	0,0977
W2	0,7947	0,0019	0,7928	0,3671	0,3387	1,0883	0,0900	0,1147
W3	0,5631	0,0007	0,5623	0,2554	0,2391	1,0844	0,1067	0,0572
Only Synthetic Data								
W1	0,7792	0,0163	0,7630	0,3809	0,3126	1,1124	0,0234	0,0977
W2	0,7949	0,0020	0,7928	0,3671	0,3386	1,0883	0,0900	0,1147
W3	0,5625	0,0008	0,5617	0,2554	0,2391	1,0844	0,1067	0,0572

Since the class distribution of the dataset is balanced, it is sufficient to use accuracy as a performance measure but seeing the results of other evaluation criteria is also important to support the reliability of the evaluation. When the results were examined, it was seen that the success rates of the studies using the original dataset were lower. Since the reason for this was thought to be that the data set was low, synthetic data was created and reclassified. This way, it was observed that the success rates were higher. In addition, considering that it would increase the success rates, statistical values of the datasets were taken, and it was observed that the success rates increased. When the success comparisons of the results were made, the success rates of the applications in which the decomposition process was made as 10-fold CV were found to be higher. When the attribute selections were com-pared, it was observed that the success rates obtained by using statistical values were higher than the others. When the classification methods were compared amongst themselves, the highest success rate was obtained using SVM. By applying additional statistical methods as pre-treatment to the data, the above mentioned decomposition methods and success rates reached 100% score for all classification methods.

Table 4: Average achievements using all features

Data	Class. Methods	CV				%80 Train - %20 Test			
		Acc	TR	F-Score	G_mean	Acc	TR	F-Score	G_mean
Raw Data	DT	0,933	0,931495	0,930233	0,950548	0,667	0,656746	0,933333	0,935414
	SVM	0,983	0,984127	0,97561	0,9759	0,958	0,958333	0,933333	0,935414
	KNN	0,967	0,966583	0,952381	0,963307	0,958	0,958333	0,933333	0,935414
Raw Data + Synthetic Data	DT	0,933	0,983333	1	1	0,667	0,979167	1	1
	SVM	0,983	1	1	1	0,958	1	1	1
	KNN	0,967	1	1	1	0,958	1	1	1
Only Synthetic Data	DT	0,933	1	1	1	0,667	0,833333	0,75	0,810093
	SVM	0,983	0,900794	0,869565	0,912871	0,958	0,875	0,842105	0,901388
	KNN	0,967	0,984127	0,97561	0,9759	0,958	1	1	1

Table 5: Success averages obtained when the dataset is processed statisticaly

Data	Class. Methods	CV				%80 Train - %20 Test			
		Acc	TR	F-Score	G_mean	Acc	TR	F-Score	G_mean
Raw Data	DT	1	1	1	1	1	1	1	1
	SVM	1	1	1	1	1	1	1	1
	KNN	1	1	1	1	1	1	1	1
Raw Data + Synthetic Data	DT	1	1	1	1	1	1	1	1
	SVM	1	1	1	1	1	1	1	1
	KNN	1	1	1	1	1	1	1	1
Only Synthetic Data	DT	1	1	1	1	1	1	1	1
	SVM	1	1	1	1	1	1	1	1
	KNN	1	1	1	1	1	1	1	1

CONCLUSION

The applications of machine learning algorithms in the field of agriculture are increasing day by day. Evaluating water stress with traditional irrigation timing techniques was insufficient due to high costs and installation difficulties. Therefore, there is a need for automated techniques to monitor crop water condition which will provide fast and reliable estimates. As a result of the study, it is seen that the classification methods applied to spectral reflections obtained from safflower leaves are important in terms of distinguishing safflower from water stress. Measurements were taken in the environment where the safflowers were grown. In order to in-crease the classification accuracy, the most appropriate attributes were tried to be selected. Due to the nature of feature extraction techniques, the complexity of the data sets makes the analysis difficult. The data set was pre-treated with the specified size reduction techniques and the most suitable size was determined using SVM, KNN and DT classification algorithms. The highest success rate was obtained by using SVM when the methods of classification were compared with each other as predicting accuracy. In line with the results, it was observed that size reduction techniques increased the success rate as expected. As can be seen from the performance of the results, it is possible to determine the ratio of safflower water by spectral reflections in safflower leaves. It is quite difficult to compare the performance of the studies performed with the methods encountered in the field due to reasons such as different classifier models, different types of hits and different feature vectors used in classification.

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Author contributions

Data Set was obtained from GAPTEAM. This study on the obtained data set was done by a single author.

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Author Queries???

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