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# Identification of RF Signals Based on 1-D Local Binary Pattern

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# تحديد إشارات الترددات الراديوية بناءً على النمط أحادي البعد ثنائي الموضع

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**Abstract:**

A novel technique to enhance the security at physical layer of wireless networks is introduced in this work. The technique is applied based on the usage of Radio Fingerprinting (RF) for Bluetooth (BT) signals emitted from BT transmitters. The technique which is Local Binary Pattern (LBP) is applied to extracting the features of RF signals. The method generated Histocount and Histogram of the transient portion of BT signals. Sixty records from each transmitter were subjected to the 1-D LBP technique. The transmitters, which are six transmitters, were classified and identified via extracted statistical features from the count of the histogram of the signals. The third of extracted features data are uploaded to a learning machine system for training. The rest of the data were used to test the classifiers. Four classifiers were applied to the train and test data to identify the subjected transmitters. The results demonstrate the effectiveness of the applied methods and the powerful of the implemented classifiers.

**Keywords:** 1-D LBP; BT signal; Histogram; RF signals; Classification.

**الملخص:**

أستخدمت, في هذه الورقة, طريقة جديدة لتعزيز مستوى الامان للطبقة الفزيائية في شبكات الاتصالات اللاسلكية. طبقت الطريقة لتلائم أستخدام بصمات الترددات الراداياوية لاشارات البلوتوث. هذه التقنية والتي تسمى تقنية النمط الثنائي المحلي, طبقت لاستخلاص ميزات اشارات الترددات الردياوية. الطريقة عملت على إنشاء التوزيع التكراري وعدد التوزيعات للاجزاء الانتقالية لاشارات البلوتوث. ستون تسجيل ملتقطة من كل باعث طبقت عليها هذه الطريقة في أتجاه واحد. هذه البواعث وهي عبارة عن ستة بواعث صنفت وتم التعرف عليها بواسطة خواص احصائية استخرجت من التوزيع التكراري للاشارات . ثلث هذه الخواص أستخدمت لتدريب المصنفات للتعرف على الاشارات المرسلة من كل جهاز, بينما أستخدم ثلثي الخواص لاختبار عمل المصنفات. عدد اربعة مصنفات تم تدريبها واختبارها للتعرف عل الباعثات. أثبتت النتائج فاعلية الطرق المطبقة وقدرة المصنفات المستخدمة.

**الكلمات المفتاحية:** نمط ثنائي محلي وحيد الاتجاه, أشارة بلوتوث, التوزيع التكراري,أشارات الترددات الردياوية, التصنيف.

## Introduction

The extraction of signals features plays a significant role in the identification of signals, and their emitters. These signals can be voice signals, vibration signals, or radio frequency signals, etc. The extraction of signals features can also be defined as a process by which the data or the behaviors of signals are transformed into interpreted informative, numerical or statistical metrics. The extracted metrics from a signal represent the finger-printings or the characteristics of the signal. These finger-printings compose a set of input data for classification, detection, and analysis processes. Many techniques were used to extract the signals features, such as time-domain analysis, frequency-domain analysis, and time-frequency techniques. The time-domain analysis is a time-based technique analyzes signals over the time to obtain statistical criteria, such as the statistical central tendency measures, and related measures that include skewness, kurtosis, variance, and standard deviation. The time domain features are extracted from surface electromyography (SEMG) signals. The study presents significant of time-domain features and their applications in this field [1]. Features extraction from ECG signal in the time domain, time–frequency domain, and sparse domain is presented in [2]. The features are used as input to machine learning and deep learning models for applications. The frequency-domain analysis is considered as one of effective methods that are used to extract features of signals. It starts by transform the signal into frequency domain by using some technique such as Fast Fourier Transform (FTT), and time frequency energy distribution. The later approach was used to extract features of wave signals for structural health monitoring [3]. The 1-D Local Binary Pattern (LBP) is applied to the Bluetooth signals, for the first time, to extract the signals' features. The 1-D LBP is considered as Time-Domain Analysis technique. Successive processes are implemented before applying the LBP. These processes are staring from the data collection passes through the signals preparation, up to implement of the 1-D LBP. The last process is the identification and classification of the input signals based on different four classifiers.

During the Identification and classification of the RF signals, there is some deficiency in the features extracting; that is because of the interference between the features' values of the RF signals that transmitted from different devices. This interference directly affects the detection, identification, and classification processes, where many transmitters are misclassified. Many techniques were used to extract the signals features, such as time-domain analysis, frequency-domain analysis, and time-frequency techniques. All of these techniques yielded low test classification percent during the learning machines applications. Usage of different features extraction techniques will lead to reinforce the efficiencies of the stages that follow the features extraction stage in the learning machine classification procedure. Consequently, this will improve the wireless network security, which is responsible for protection the communication networks from some threats such as signal interception, spoofing or jamming. The widely usage of the wireless networks, in this era, led to prioritizing the security of wireless networks, where there is significant role of this networks, not only in communication sector, but also in most of other sectors such as trading, education, industrial, administration etc, so that huge amount of data are transferred and interchanged via wireless networks. Therefore, low net security definitely leads to threaten of signal interception, spoofing or jamming. Consequently, the identification of wireless transmission devices grantees safely transmitted information to the receiver. Because of the importance of the wireless networks security, the successive applied methods need to be treated to achieve: Appropriate implementation and a satisfied analysis and results, accurate and repute extracted features, high percent of correct classification and identification of transmitters, and precise recognition of different signals.

In section two the applied methods are demonstrated. The 1-D LBP, which is considered as the main applied technique, in this work, is implemented to the uploaded data in section three. In section four, the transmitters are classified based on four classifiers. The study is concluded in section five.

## Methods

Successive processes were applied to accomplish the considered methodology of this study. These processes start from the collection of the subject real data which is BT signals, passing through preparation processes, such as filtering and normalization processes of the collected data, up to the implementation of 1-D LBP, and machine learning artificiel intelligence.

In the data collection process, the real BT data was captured in an appropriate laboratory environment. The laboratory is completely isolated, where no instruments, or devices are running. The carrier frequency range of the captured signals is between 2400 MHz and 2483.5MHz.

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The received signals are captured by the Oscilloscope. The captured signals are uploaded to a computer to manipulate it. The captured signals are transformed from analog to digital signals by a converter that has at least 4.8 GHz sampling frequency. Once the signals are transmitted, filtering process is needed; because of the existence undesired frequency components that the recorded signals have. The undesired frequency components are amalgamated to the captured signals during recording signals by the oscilloscope. Sample of the collected BT signals is shown in Fig.1.

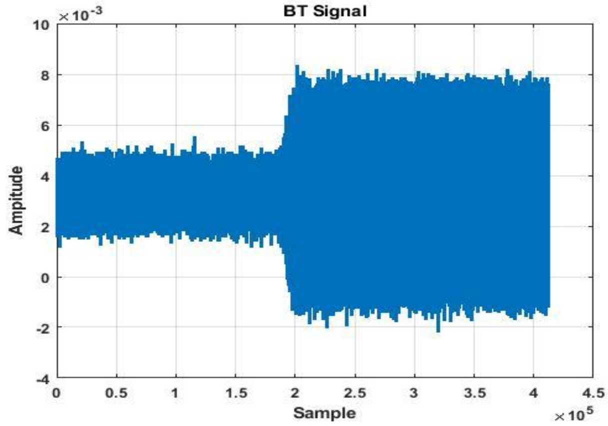


**Figure 1.** Typical samples of the collected BT signals

Even though the existence of appropriate laboratory conditions, the captured signals still suffer from unwanted signals, such as noise signals and disturbance signals. These undesired signals come from the mobile phones and the instruments that utilized to collect the studied signals. Successive processes are done to prepare the captured signals before implementing the 1D-LBP.

The first preparation process of the captured data is to get rid of unwanted components. A Band Pass Filter (BPF) is utilized to remove these unwanted signals. A band-pass filter allows some components to pass among whole components. The passed components are located in a specified band of frequencies, while the components that have frequencies above or below this band are rejected. In our work, BPF has a cut off frequencies 2400 MHz and 2485, where the band of the carrier frequency of the BT signals is located.

The second process in the collected data preparation is the centring and normalizing of the filtered signals. The purpose of this process is to make the center of all signals is zero, and the highest and lowest amplitude of all signals are one, and minus one, respectively; so that all signals will have the same range of amplitudes. That makes the comparison between the studied signals easier. The BT signals are divided into three parts, namely the noise portion, the transient portion, and the steady state portion. These parts are shown in Fig.2.

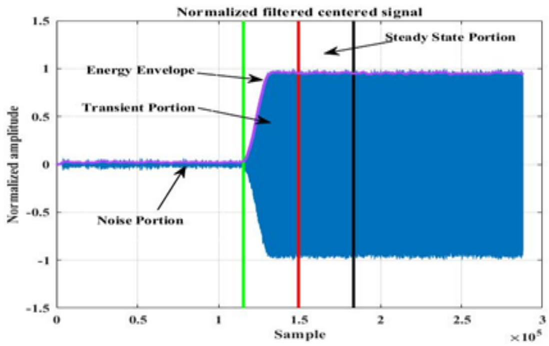


**Figure 2.** The three portions of a BT signal

The portions' detection of the BT signals means the finding of the start and the end of each portion. Different methods can accomplish this issue. These approaches and techniques are used to detect the start and the end of the transient stage; because the end of the noise portion is the beginning of the transient signal, while the start of steady state portion is the end of the transient signal. The stages of the signals, in this study, are detected by means of the Energy Envelope technique, which is obtained by taking the absolute of the Hilbert transform of the signal. The generated energy envelope is illustrated in Fig. 2. The detection of start and end of the transient portions are done by exploiting the changing of statistical features along the signal energy envelope. In this research we consider the transient portions of the signals. Many techniques and approaches can be applied to extract the features of the detected transient signals, such as the Empirical Mode Decompression technique (EMD) [4, 5, 6], Hilbert Spectrum of signals [7, 8], and Variational mode decomposition (VMD) method [9]. All of these techniques are implemented to the detected transient signals to prepare the signals for extraction their features. In this study, and 1-D Local Binary Pattern technique is applied to the detected BT transient signals' features.
The local binary pattern is a technique used to extract signal features based on the differences between the value of the signal at a sample and its neighbours [10, 11, 12]. The 1-D LBP distinguishes the unvoiced speech signals and the voiced components by using distinguishing features extracted from histogram bins [13]. A facial image representation based on local binary pattern (LBP) texture features, and color-based Local Binary Pattern (LBP) image analysis for face recognition was presented in [14,15], respectively. The human face organs analysis related tasks were recognized by implementing The 2D LBP [16]. The 1-D LBP technique checks every single value of the signal by taking in accounts its neighbourhoods and utilities the value of the center sample value signal as a threshold for the neighbourhoods. If the neighbour value is less than the value of the center sample, the value of the neighbour set to 0; otherwise it will set to 1. So that the 1-D local binary pattern code for a neighbourhood is then constructed. The decimal value of the LBP binary code presents the local structural data around the center value. The histogram of the 1-D LBP pattern signal illustrates how the deferent patterns appear in a given signal. The distribution of the generated patterns represents the whole structure of the signal. The 1-D LBP operation of a sample signal value is given in the following formula:

$$\boldsymbol{LBP_p}(\boldsymbol{x}[\boldsymbol{i}]) = \sum_{r=0}^{p/2-1} \left\{ \boldsymbol{f}\left[\boldsymbol{x}\left[\boldsymbol{i}+\boldsymbol{r}-\tfrac{p}{2}\right] - \boldsymbol{x}[\boldsymbol{i}]\right] \mathbf{2}^{r} + \boldsymbol{s}\left[\boldsymbol{x}[\boldsymbol{i}+\boldsymbol{r}+\mathbf{1}] - \boldsymbol{x}[\boldsymbol{i}]\mathbf{2}^{r+\frac{p}{2}}\right] \right\} \quad \textbf{(1)}$$

The results can be

$$\boldsymbol{f}[\boldsymbol{x}] = \begin{cases} \mathbf{0} & \boldsymbol{x} < 0 \\ \mathbf{1} & \boldsymbol{x} \geq \mathbf{0} \end{cases} \quad \textbf{(2)}$$

where $x[i]$ is the signal, p is the number of neighbours. The Sign function $[x]$ transforms the differences to a $P$-bit binary code.

## Results and discussion

After applying the aforementioned preparation processes, the 1-D LBP was implemented to the transient signals. The purpose of the implantation is to extract the features from the signals, consequently, identifying the studied transmitters from which different BT signals were transmitted. The features of each record (BT transmitted signal) are generated from the Histogram or the Histcount of the transient signal, where the Histogram is a graphical visualization of the record signal distribution. The Horizontal axis represents numeric data intervals or bins, whereas the Vertical one represents the counts, or percentage of data for each bin. These counts can be easily taken from the Histocount diagram, where the exact value of each count that associated with a certain bin can be determined, consequently, sets of

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partition data can be yielded as output arrays of counts per bin. Fig. 3 represents typical forms of the Hisotcount and the Histogram of one record taken from a transmitted BT signal of a certain transmitter.

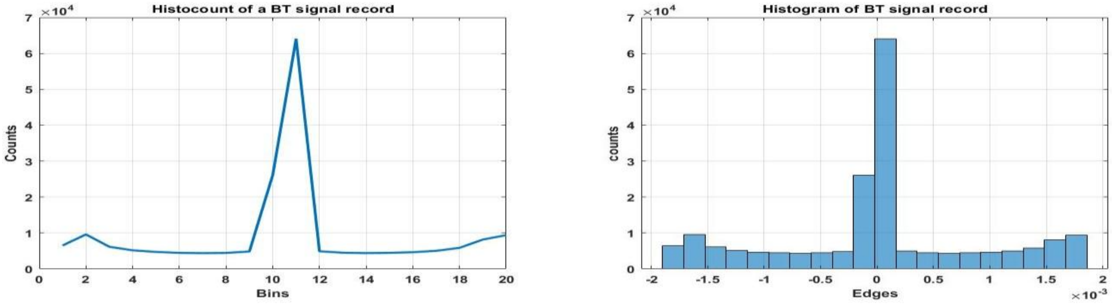


**Figure 3.** Typical forms of Histocount and Histogram of BT signal

The number of counts in Histcount is 20 counts, which is equal to the number of interval in the Histogram. The histograms of the sixty records of the six studied transmitters are individually depicted in Fig. 4. It's inferred from the figure that each transmitter has its own unique histogram shape. This gives us a primary impression of the possibility of distinguishing between different transmitters.

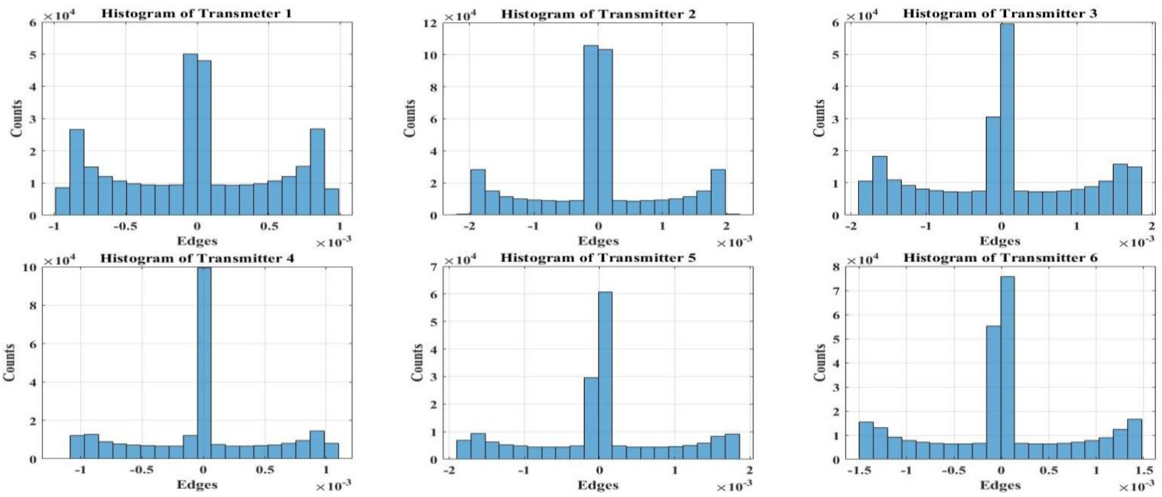


**Figure 4.** The histograms of BT signals transmitted from six transmitters

The Histogram visualizes the data distribution, whereas the values of the data can be extracted from the Histocount, where the statistical features can be extracted from. Six features are extracted from each count of the whole data. The extracted features from each count are Mean, Skewness, Kurtosis, Standard Deviation, Entropy, and Maximum values. Each exctracted feature is prepared in a matrix form. In which the rows represent the transmitters (classes), whereas the columns represent the number of records that taken from the transmitters.

The extracted features' matrices are merging in a form by which the classifiers can be applied. The Matlab built in function (reshape) is used for this purpose. By this function the extracted features data can be divided into trained and tested groups. The trained group, which represents a percent of the data, is utilized to train the classifiers before test them via the rest of the data. In this study, the extracted features trained data represents one-third of the data, whereas the tested data is two-thirds of the data. Before implementing the classifiers to the extracted features data, it is possible to check the feasibility of the extracted features in advance. This can be accomplished by the Box plot diagrams that are shown in Fig. 5, where

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four features for six transmitters are illustrated. The features are Entropy, Kurtosis, Mean, and Standard deviation.

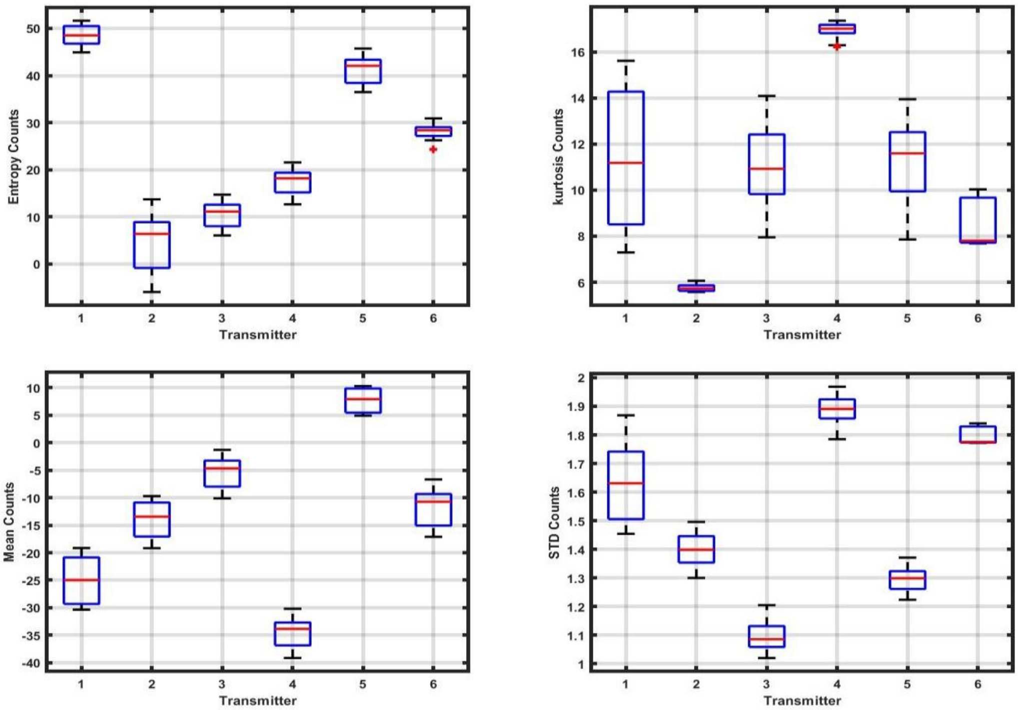


**Figure 5.** Box plots of Entropy, Kurtosis, Mean, and STD features.

It's clearly deduced from Fig. 5, that there are three robust or separable features, and one brittle feature. These features can compensate the deficiencies of each other. For instant, in the box-plot of mean feature the sixth transmitter can't be distinguished from the second transmitter; because they have mostly the same range of mean feature, which is around (-15). This deficiency of the mean feature can be compensated via Entropy features, where the entropy values of transmitter six and transmitter two are completely separated, whereas transmitter three and transmitter two are partly separated by entropy feature. But these classes are completely separated by the standard deviation feature. So it is predicted to get considerable percentages of training and testing classification.

Twenty records out of sixty are uploaded to train models; the purpose of the training process is to learn the classifiers for testing stage. Four classifiers are trained by the uploaded train data. The applied classifiers, in this study, are Support vector machine, Linear Discriminant analysis, K-nearest neighbour, and Decision tree. The results of the training process can be checked before implementing the testing. Scatter plots, confusion matrix, and Receiver-operating characteristic curve (ROC) or Area under the curve (AUC) are visualized criteria used to evaluate the learning of machine. The scatter plots of two different relationship between Standard deviation feature Vs. Entropy feature, and Standard deviation feature Vs. Kurtosis feature are illustrated in Fig. 6.

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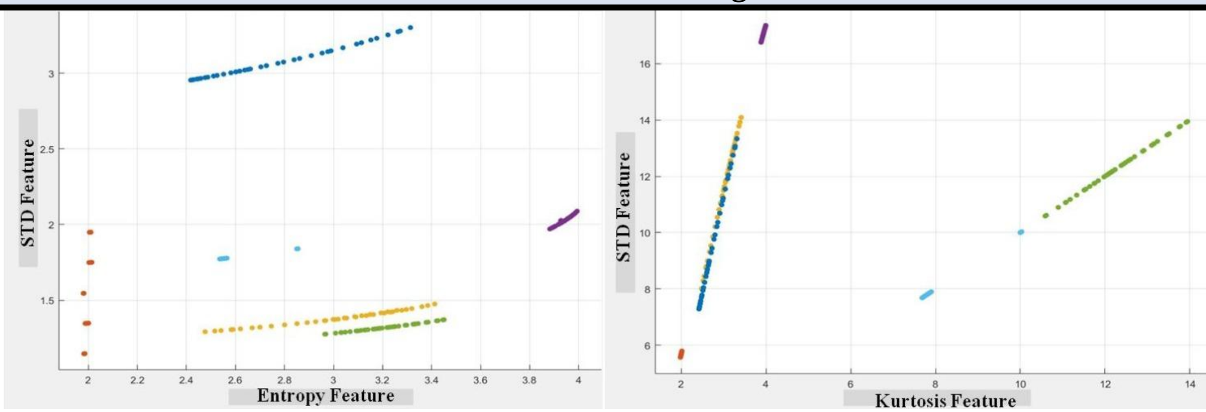


**Figure 6.** Scatter plots of STD Vs Entropy, and STD Vs. Kurtosis

The STD and Entropy intersection, in Fig. 6, demonstrates separable transmitters, where each color in the scatter plot represents the records of a certain transmitter. Right there, there are six colors' groups for six different transmitters, whereas the STD and Kurtosis intersection demonstrates merging transmitters' records, where the colors of the scatter plot are not completely separated. This means that one or both features are weak features. There are six statistical features; therefore, more scatter plots can be checked before implementing the training and testing processes. The training process of the four applied classifiers demonstrated high degree of machine learning capability, as shown in Table. 1.

**Table. 1** shows the machine learning training Accuracy percents

| Classifier | Training Accuracy |
|---|---|
| Decision Tree | 1 Tree Accuracy: 100.0% Last change: Disabled PCA 6/6 features |
| Linear Discriminant | 1 Linear Discriminant Accuracy: 100.0% |
| Support Victor Machine | 6 SVM Accuracy: 100.0% |
| K-Nearest Neighbors | 2 KNN Accuracy: 100.0% Last change: Fine KNN 6/6 features |

The learning machine results i
these classifiers are trained via 20 records of all transmitter classes, Fig. 7 illustrated the predicted and true classes training test of the Decision tree, where the vertical and horizontal axes represent the transmitter devices (classes) number. The Figure shows the training confusion matrix of decision tree classifier.

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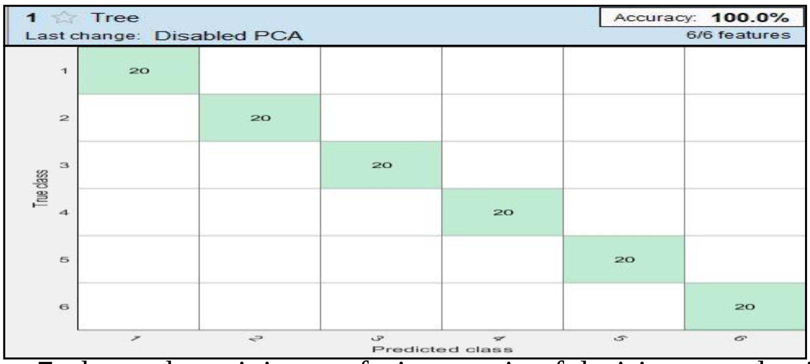


**Figure 7.** shows the training confusion matrix of decision tree classifier

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Once, the classifiers are trained, and the results of machine learning are checked, the rest of the data (transmitters' features), which is 40 records of each transmitter, can be uploaded to the trained classifiers as a test data. The implementation of the four classifiers to the test data yielded four confusion matrices. The resultant confusion matrices give the percentages of the accuracy of applied classifiers. as shown in Fig. 8.

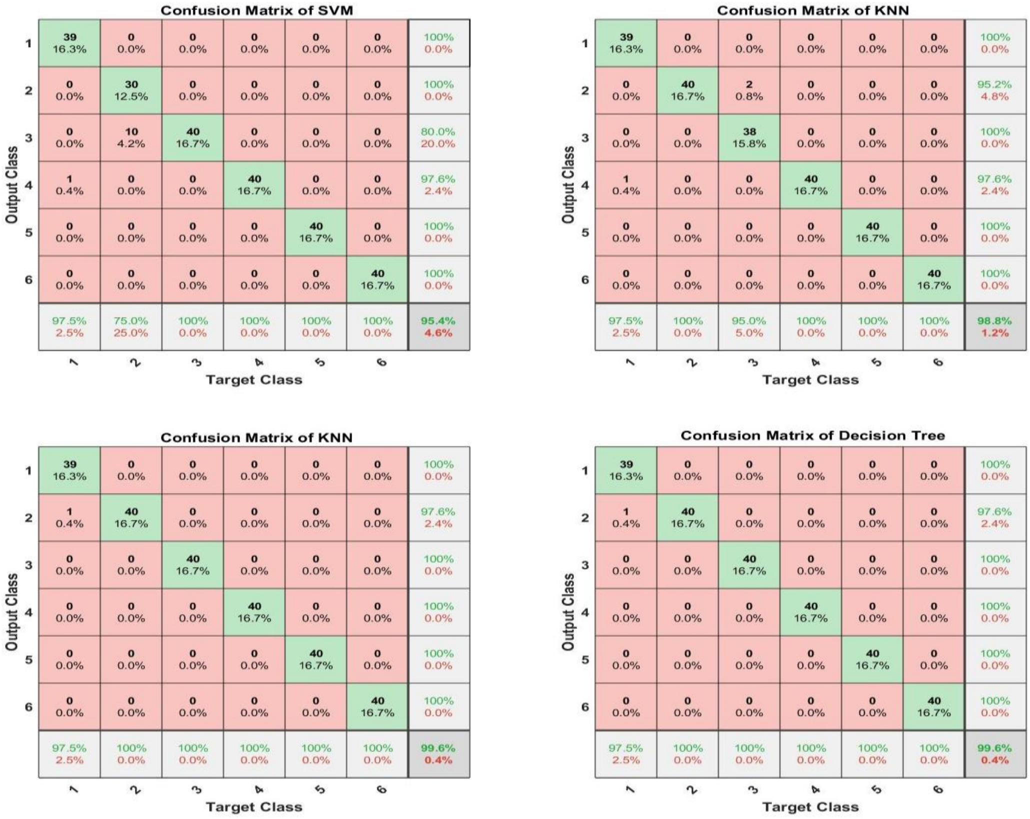


**Figure 8.** Testing confusion matrices of the implemented classifier

The testing process yielded overall percentages of identification of the transmitters for the applied classifiers. The percentages were 95.4%, 98.8%, 99.6%, and 99.6% for Support vector machine, Linear Discriminant analysis, K-nearest neighbour, and Decision tree classifiers, respectively. The testing confusion matrices don't only demonstrate the overall percentage of the identification process but also illustrate the accuracy percentage of the true classified records for each transmitter. This is shown in the percentage column of each testing confusion matrix.

## Conclusion

1-D LBP technique was applied to BT signals transmitted from six different transmitters. Sixty records are collected from each class to generate data base of 360 records. The data base is prepared before implementing the 1-D LBP approach. The preparation processes were filtering, centring, normalizing of the data. The prepared data was uploaded to the 1-D LBP to generate the Histogram and Histocount of each record. From which six statistical features were extracted for each record. The one-third of the extracted features was uploaded to classification software of Matlab for learning machine training. After training process a testing process is applied to rest of the data. The identification approaches demonstrate the effectiveness of the applied methods, and the powerful of the applied classifiers.

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