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CLASSIFICATION OF ORIGINAL AND COUNTERFEIT GOLD MATTERS BY APPLYING DEEP NEURAL NETWORKS AND SUPPORT VECTOR MACHINES

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Abstract: Gold is one of the most counterfeited precious metals. The color of copper is like gold. For this reason, copper is one of the most used materials for color counterfeiting. When the chemical properties are concerned, wolfram is like gold (density of gold and tungsten are 19.30 g/ml and 19.25 g/ml, respectively), so it can be used as a chemical counterfeit. The purity of gold can be determined by X-ray, but this method is costly. The current low-cost methods of jewelers have been experimented with for counterfeit gold detection in this paper. When a gold matter is hit by a subject, the sound frequency is higher than the frequency of sound when the same experiment is done with copper. Furthermore, counterfeit gold color is brighter than real ones. The color of gold is unique, and it is called "gold yellow". In this research, by employing sound and image processing, counterfeit and original gold are differentiated. For the image processing part, first a Convolutional Neural Network (CNN)-based toolbox for segmenting the gold material is applied. Then, deep CNNs for differentiating the color of the gold and copper materials are employed. Promising results are achieved with both sound and image processing techniques.

Keywords: counterfeit gold differentiation, sound processing, image processing, support vector machines, convolutional neural network, image segmentation

Yapay Sinir Ağları ve Destek Vektör Makineleri Kullanılarak Gerçek ve Sahte Altın Sınıflandırılması

Öz: Altın, en çok taklit edilen değerli metallerden biridir. Bakırın rengi altına benzer. Bu nedenle bakır, renk sahteciliği için en yaygın kullanılan malzemelerden biridir. Kimyasal özellikler söz konusu olduğunda, volfram altına benzer (altın ve tungstenin yoğunluğu sırasıyla 19.30 g/ml ve 19.25 g/ml'dir), bu nedenle kimyasal bir sahte olarak kullanılabilir. Altının saflığı X-ray ile belirlenebilir, ancak bu yöntem maliyetlidir. Bu yazıda, sahte altın tespiti için kuyumcuların mevcut düşük maliyetli yöntemleri ve sahte parayı tespit etmek için kullanılan düşük maliyetli yöntemler denenmiştir. Bir yüzeye altın bir madde çarptığında, ses frekansı aynı deney bakır ile yapıldığındaki sesin frekansından daha yüksektir. Ayrıca, sahte altın rengi gerçek olanlardan daha parlaktır. Altın rengi benzersizdir ve "altın sarısı" olarak adlandırılır. Bu araştırmada ses ve görüntü işleme yöntemleri kullanılarak sahte ve orijinal altın ayrımı yapılmıştır. Görüntü işleme kısmı için, önce görüntüden altını segmentlere ayırmak için CNN tabanlı bir araç kutusu uygulanır. Bundan sonra, altın ve bakır malzemelerin rengini ayırt etmek için derin Evrişimli Sinir Ağları kullanılır. Hem ses hem de görüntü işleme teknikleri ile umut verici sonuçlar elde edilmektedir.

Anahtar Kelimeler: sahte altın farklılaşması, ses işleme, görüntü işleme, destek vektör makineleri, evrişimli sinir ağı, görüntü bölümlendirme

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1. INTRODUCTION

In the banking sector, it is critical to know whether the delivered matter is counterfeit or not upon delivery (Can et al., 2015). At this point, the ability to sell the gold bought from a bank at any point would be a great convenience for a customer. However, since there are thousands of branches for banks, a gold acceptance system must be low cost and have very high accuracy. In the current system, the purity of gold and whether the matter is original or counterfeit gold could be determined by experts on specific days of the week and at specific branches. This situation brings customers difficulty to go to specific branches at specific times. Furthermore, the possibility of human errors and the cost of an expert can be listed as the drawbacks of the current system (Can et al., 2015).

There are two types of techniques for analyzing gold purity, destructive and non-destructive, namely (Nor et al., 2019). Destructive techniques dismantle the gold sample by using methods such as fire assay and Inductively Coupled Plasma (ICP) (Singh 2012), (Battaini et al, 2014), (Karadjova et al.,2000), (Kinneberg et al., 1998), (Brill, 1992), (Brill, 1997), (Hanrahan, 1962). Non destructive techniques, on the other hand, will not dismantle the gold samples in the analysis. Furthermore, they can measure gold purity on the surface and the whole piece. Densimeter, weighing balance, and ultrasound devices are the instruments that could assess the gold purity of the entire matter (Raw, 1997), (Smrcka et al., 1965) and (Eames et al., 2015). Meanwhile, X-ray Fluorescence (XRF) and electronic pen could measure the gold purity only from the surface (Majcen, 2002), (Piorek et al., 2013), (Rastrelli et al., 2009), (Schaffer, 2003) and (Jalas et al., 2002).

Figure 1:
A gold bar plated with tungsten is demonstrated (Nor et al., 2019).

From the non-destructive methods, XRF is the most commonly applied technique. Piorek et al. determine the gold purity ratio by comparing L-alfa and L-beta X-ray beams by employing XRF technology in article (Piorek, 2005)., and US 2013/0202083 A1 United States patent (Piorek et al., 2013). In this system, the XRF spectroscopy method is used to measure the characteristic L-beam ratio and the system decides whether the test object is pure gold or a mixture of gold and other metals by preserving the structure of the object. This system is costly because it uses X-ray beams. Metal component identification by XRF analysis is employed in another United States patent US 2014/0201033 A1 (Crain and Suarez, 2014). Researchers used ultrasound and electrical conductivity measurement tools to determine whether the cross-section was changing or not. This system makes metal transactions easy as far as instant purity measurement and instant price evaluation are concerned. The drawback is again the high cost of usage of X-ray beam technology. Densimeter and weighing balance methods are direct applications of Archimedes' principle. These methods will detect the gold matter in the air and in distilled water. After that, the liquid in the glass will be employed to estimate the water temperature. Generally, the distilled water temperature is very close to the environment temperature. The density of distilled water will be computed with equation of Kell (Specification, 1991). The densimeter's software determines the density, and the gold purity of the matter can be calculated. The difference between these methods is that, although they rely on the same principle, the weighing balance method requires an hour in laboratory tests. Densimeter, on the other hand, measures purity instantly, but it is more expensive (around 1000$).

Table 1. The comparison of gold purity measurement methods.

Method	Response Time	Cost	Measuring From	Deep Learning	Destruct
XRF	Instant	H	Surface	No	No
Densimeter	Instant	M	Whole	No	No
Weighing Balance	1 hour	L	Whole	No	No
Ultrasound	Instant	H	Whole	No	No
Our study	Instant	L	Surface (Image), Whole (Sound)	Yes	No

As mentioned before, XRF can be used to measure purity from the surface and near-surface. If the element is covered with an enough depth of gold layer (see Figure 1), then the XRF could not detect the other elements inside the gold (İsmail et al, 2018). Especially Tungsten has a very similar density with gold and it can be used to create counterfeit bars and coins. These items not only look like real gold and but also have the correct weight. However, the sound velocity of any metal could be estimated by using ultrasonic pulses and the ultrasound device could identify counterfeit gold bullion coins and bars. However, the ultrasound device is also an expensive device.

In this research, a deep learning-based software that automatically detects counterfeit gold by using the image and sound processing is developed. Experiments were carried out with bare gold and gold in mika. Image processing techniques are applied for one gram gold in mika, whereas bare one gram gold is discriminated from fake metals by applying both image and sound processing techniques. CNN-based automatic image segmentation was also developed to filter metal in the pictures and Convolutional Neural Networks, shallow Neural Networks and Support Vector Machine methods were implemented and compared with simpler machine learning algorithms. Furthermore, we filter the sound before feature extraction. Manually segmented and original gold and copper images were added as a public dataset for researchers studying in the field of matter segmentation and classification. The deep learning methods obtained higher accuracies when compared to the previous studies in the literature.

2. RELATED WORKS

The gold purity methods can be examined under four main criteria. The first one is whether the method is destructive or non-destructive. Most of the widely used gold purity detection techniques are non-destructive. As mentioned before, another important criterion is where the method is measured from the material. XRF technology can measure only from the surface, which makes it vulnerable to attacks such as stuffing other materials inside gold material. Ultrasound, weighing balance, densimeter methods can measure the whole material. Our method has two components. The image processing component can detect the different materials on the surface, whereas the sound component can detect density changes by examining the impact sound frequency.

The gold purity detection method must also be cheap. Because the aim is to integrate the system into every ATM for accepting 1 gram gold and return the corresponding money. If the system is expensive, the cost would be too high and the banks can choose to continue with the human expert system. When the common techniques are examined, they are not cheap (XRF (around 10k \$), Densimeter (1k\$), Ultrasound (1k\$)). The proposed method is composed of one sound recorder and one camera which are around 100\$. The gold purity systems should respond instantly, which eliminates laboratory-based long techniques such as weighing balance.

As we can see from the literature (see Table 1), our method is cheaper, it has instant response, it can detect anomalies from the surface and in the whole material. It is not destructive. Deep learning usage increases the prestige of our product when compared to its competitors.

3. DESCRIPTION OF THE DATASET

3.1 Sound Classification

In this study, the same sized bare gold and bare copper were used. I tried to reveal the difference between bare original gold and bare copper. The proposed method tries to discriminate the sound of impact after a free fall from a specific height (15 centimeters). I tested our methods on bare gold and bare copper. Impact sound was recorded by using a Samsung Galaxy S5 mobile phone. There was not any specific noise when the signals were recorded. I experimented with free fall ten times for gold and ten times for copper from 15 centimeters height. The sounds could be accessed in the plain_sound folder.

Figure 2:
Original images of gold and copper are demonstrated. In the top left, there is a bare copper sample, in the top right, there is a bare gold sample. In the bottom row, copper inside mika and copper inside gold samples are shown left to right.

3.2 Image Classification

With the Nikon D90 camera, I experimented differentiation of gold and copper from high-resolution image processing. An equal number of high-resolution pictures from bare counterfeit and original gold were recorded. 30 bare gold and 30 bare copper pictures were taken (see Figure 2). Distance to the camera lens, angle and amount of light was equal for each case.

The more difficult task is to classify gold and copper inside mika. Mika can reflect or absorb light which makes it more challenging to discriminate the color of original gold from counterfeit gold. Pictures from sunlight, fluorescent light and dim light environments were taken. High accuracies could not be obtained from direct sunlight and direct fluorescent light environments because mika reflects light and shines (Can et al., 2015). In the dim light, I experimented on 30 gold in mika and 30 copper in mika pictures.

3.3 Image Segmentation

To use a CNN-based segmentation toolbox dhSegment (Oliviera et al., 2018) to detect metal parts in the image, Image dataset which has annotations of two object classes was formed. The first class is the background, which is the field between the metal and image borders. This class is colored with black color. The second class is the metal fields, and they are marked with red. 60 images (30 copper inside mika and 30 gold inside mika) were marked with the abovementioned annotations. An example image with a corresponding annotation are demonstrated in Figure 3.

For recreation purposes, a public dataset was formed. Image and sound data are divided into 80% training and 20% test partitions. It could be accessed at https://github.com/ysaidcan/counterfeit_gold_detection. It has original images and annotated label files for both training and test partitions. It could be used to classify both sound and images and segment metal inside images.

Figure 3:
An example image with corresponding annotations is demonstrated.

4. COUNTERFEIT GOLD DETECTION SYSTEM

4.1 Sound Processing Module

There was not any specific noise when I recorded the signals. It is assumed that there is broadband noise, so a frequency-selective filter will have no discernible effect. Wavelets were selected to denoise the sound. Wavelet transform, transforms sound amplitudes in a few large-magnitude wavelet coefficients and small value coefficients are determined as noise and the algorithm removes them by preserving the quality of the sound. "Haar Wavelets" were chosen. MATLAB cmddenoise algorithm was used. Filtered sound can be seen in Figure 4:

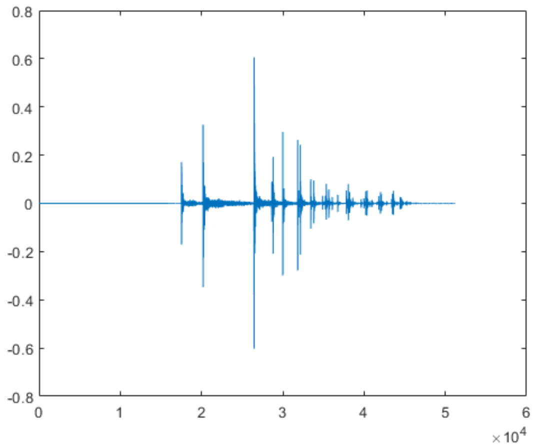

Figure 4:
Filtered Impact Sound in Time Domain

Since it is known that the frequency of impact sound is different between counterfeit gold and original gold, peak frequency was selected as the feature. Decision Tree, kNN, Neural Network and SVM classifiers were employed for the sound processing module.

4.2 Image Processing Module

In the image processing module, first, the precious metal parts from the images are automatically segmented. Then, these segments are classified by using the latest machine learning techniques.

The dhSegment toolbox (Oliviera et al., 2018) which is a public toolbox for pixel-wise segmentation jobs was used. It composes of two parts; the first part is the Fully Convolutional Neural Network (FCNN). It provided the test image as an input to the FCNN, and then it creates the map of pixel probabilities. The second part (post-processing) converts the map of prediction to the application output.

The FCNN-based dhSegment tool uses pretrained weights from commonly used models i.e. Vgg16, Unet and Resnet50, where the system could learn the high-level features (Ioffe, 2017). This improves robustness and generalization. In this way, model training time and the network complexity of the FCNN architecture were decreased drastically (Oliviera et al., 2018).

Two models were formed, by employing the pretrained Unet and Resnet50 architectures. The classification model was created for the precious metal regions. There were two different object classes: background and precious metals. The pixel probabilities of each object class were computed. A binary matrix consisting of pixel probabilities was creating for each class. By employing a connected component analysis tool, pixels formed objects for an application (Oliviera et al., 2018). After the objects were created for the metal region class, our system performance can be measured.

The raw 2D image was provided as input to CNN, whereas three components (R, G, B) that create color was calculated for each pixel. R, G, B means for each picture was further calculated. Each picture was represented as a three-length vector.

After features are extracted, data mining algorithms are used to classify counterfeit gold and original gold. In this section, the most commonly employed data mining techniques used in classification are presented. Four different algorithms were chosen: Support Vector Machine (SVM), Decision Tree, a Deep Neural Network (one output, one input and two hidden dense layers), and CNN. The first three algorithms are applied to the raw image by converting 2D matrices directly to 1D arrays. CNN is applied to the 2D images directly. These algorithms are selected because each one represents a different type.

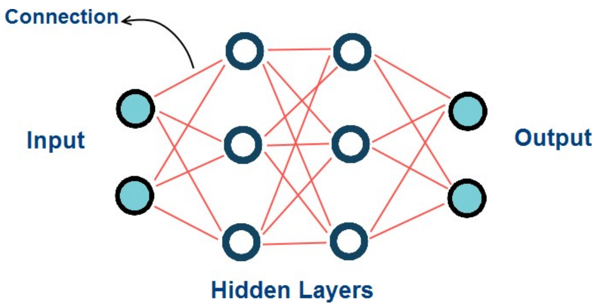

Figure 5:
ANN Model Structure.

The first algorithm is Support Vector Machine which creates decision planes that define decision boundaries. A decision plane can be defined as the line that divides objects belonging to different classes. In some classification tasks, complex decision structures are needed to separate these objects into their classes correctly. Support Vector Machines are designed to cope with these kinds of tasks. SVM rearranges objects using kernels which are a set of mathematical functions (Hill et al., 2006). The objects are mapped or transformed so that they can be easily separated by less complex lines.

The second algorithm is ANN which try to mimic biological neuron structures in the brain. They have an input layer, output layer and hidden layers (see Figure 5). Each layer has connections and weights of these connections. Iterations of neural networks are called epochs. For each new input pattern, the weights are updated by evaluating feedbacks (Hill et al., 2006).

The third algorithm is decision tree which is a machine learning tool that is used for regression or classification of both continuous and discrete variables (Caudill, 1987). The structure of the data mining model inspired its name. The decision tree mechanism is as follows: For each iteration, local regions are created recursively. It is a supervised and hierarchical model (Alpaydın, 2021). The decision tree comprised decision nodes and leaves. Each decision divides data. Low entropy divisions are created in this manner. Appropriately sized tree generation requires expert (Hill et al., 2006). Random Forest is a variation of Decision Tree which uses multiple trees instead of a single one.

The last classification algorithm is the Convolutional Neural Network (CNN). It is a Deep Learning method that takes an input image, assigns importance (learnable weights and biases) to different perspectives/things in the image, and separates one from the other (Glorot and Bengio, 2010). The pre-processing needed in a CNN is much lower when compared to other classification methods. While filters are hand-engineered in traditional methods, with enough training, CNNs could automatically learn these filters/characteristics (Ronneberger et al., 2015). The CNN architecture used in this study is shown in Figure 6.

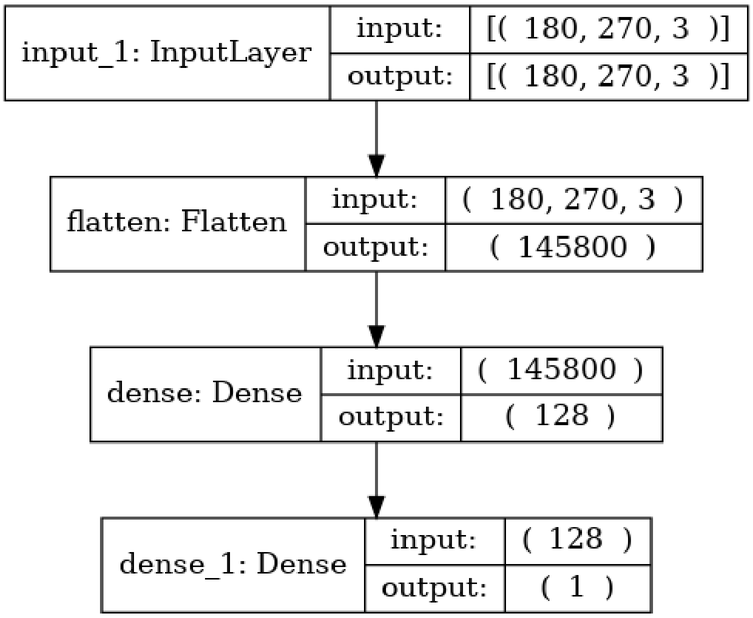

Figure 6:
The CNN architecture used for classifying precious metals.

5. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, the results for classifying gold and counterfeit gold (copper) are presented. The image processing and sound processing module results are presented separately. In the image processing module, first, the results for classifying bare gold and then the gold inside mika were presented. Before the classification of precious metal images, automatic CNN-based segmentation was applied, and its performance was presented.

5.1 Image Processing Module

The first task is to differentiate between bare gold and copper. Since there is not any cover outside these materials, differentiating them is easier when compared to differentiating precious metals inside mika.

In order to evaluate our bare precious metal segmentation system performance, two metrics are employed: pixel-wise accuracy, and Intersection over Union (IoU), which are commonly used measuring the performance of varying image processing applications. The pretrained Resnet-50 (He et al., 2016) and Unet models for each metal were used and results were extracted. They are shown in Tables 2 and 3. When the performance of different pretrained architectures were examined, the success depends on the metal type. The results for bare copper and bare gold are very close for both architectures. Furthermore, it could be stated that the metals are segmented with success when pixel-wise accuracy and IoU results.

With the Nikon D90 camera, I experimented differentiation of gold and copper from high-resolution image processing. 30 bare gold and 30 bare copper pictures were taken. The 2D image is provided as input to CNN, whereas R, G, B component average features were extracted for other classifiers. For each picture, three features were employed. K-fold cross validation was applied to ensure that our system performs high accuracies as stated in (Can et al., 2015). SVM, decision Tree, NN algorithms were used, and they are compared with the CNN algorithm. The decision tree discriminates two signals by looking at only the B component, as in Figure 7. Bare gold and copper have been classified with 100% under sunlight, lamplight and dim light environments with all algorithms.

Table 3. Bare gold segmentation results.

Pretrained Architecture	Pixel-wise Accuracy	IoU
Resnet50	94.28	77.06
Unet	97.44	87.43

Table 4. Copper in mika segmentation results.

Pretrained Architecture	Pixel-wise Accuracy	IoU
Resnet50	97.51	92.18
Unet	97.64	92.30

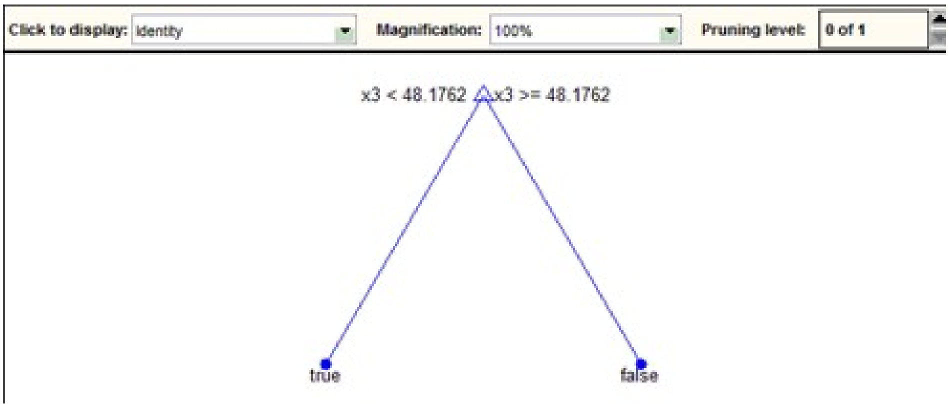

Figure 7:
Bare gold differentiation with decision tree (Can et al., 2015).

In order to evaluate our precious metal inside mika segmentation system performance, the same two metrics were used which are pixel-wise accuracy and IoU. The pretrained Resnet-50 and Unet models were used for each metal and results were extracted. They are shown in Tables 4 and 5. Although there is not a significant difference between the segmentation of gold and copper inside mika, it could be seen that these results are higher than those of bare precious metal segmentation. It could be explained by that the circular mika separates the metal from the surface makes it easier to segment these metals. The effect of pretrained architecture again changes with metal type.

In the dim light, I experimented on 30 gold in mika and 30 copper in mika pictures. SVM, decision Tree, NN algorithms were applied to classify data and they are compared with the CNN algorithm. k-fold cross validation was used. The decision tree method has the lowest accuracy. The results are demonstrated in Table 6. It is clearly shown that neural networks increased the performance of the precious metal classification task. Since CNNs are developed specifically for the images and can implement appropriate filters automatically, Convolutional Neural Networks achieved the best results. The loss function of best-performing CNN is shown in Figure 8.

Table 5. Gold in mika segmentation results.

Pretrained Architecture	Pixel-wise Accuracy	IoU
Resnet50	98.52	94.82
Unet	96.54	88.96

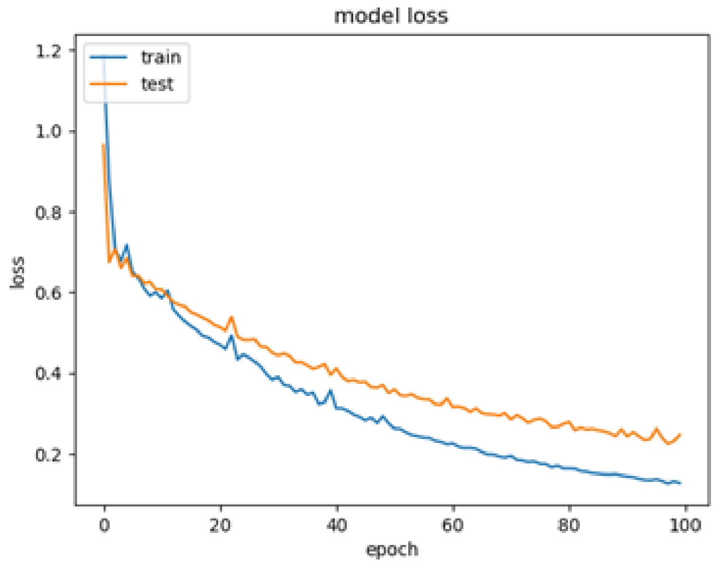

Figure 8:
The loss of CNN used for classification of metals inside mika.

Table 6. Precious metal classification results with different classifiers.

Classifier	Accuracy
Decision Tree	73.52
SVM	75.24
Neural Network	93.34
CNN	96.67

Table 7. Bare gold and bare copper identification accuracies by using the impact sound.

Classifier	Accuracy
NN	100
SVM	100
kNN	100
Naive Bayes	100
DT	100

5.2. Sound Processing Module

I experimented with free fall ten times for gold and copper from 15 centimeters height. These signals are then recorded. Wavelet denoising algorithm was employed to clear the noise for each frequency. This sound then transformed to the frequency domain. When the average was computed for gold and copper sounds, results are as follows:

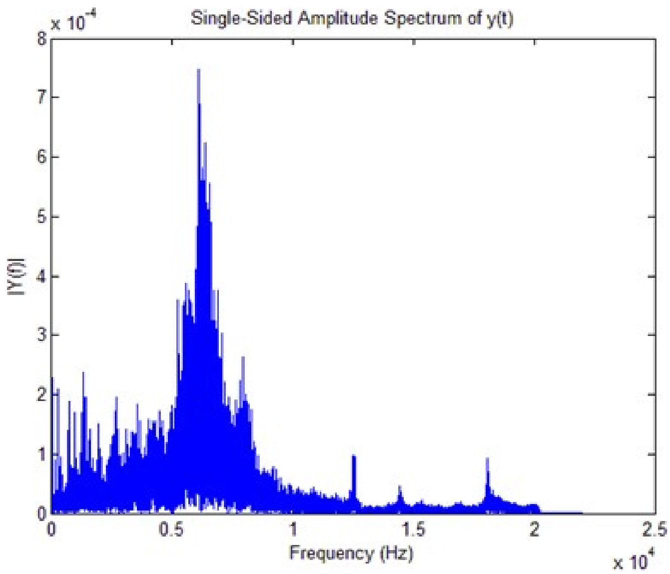

Figure 9:
Bare Original Gold, Frequency Domain Representation of Impact Sound.

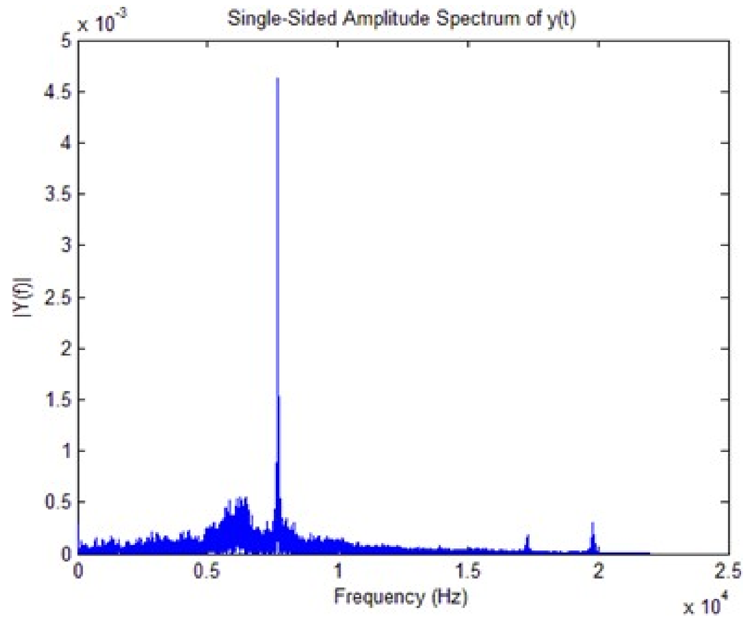

Figure 10:
Bare Counterfeit Gold, Frequency Domain Representation of Impact Sound.

It can be inferred from Figures 9 and 10, impact sound of gold peaks around 6 kHz, whereas counterfeit gold (copper) peaks around 7500 Hz. The data were divided into 80% training set, and 20% test set. K-fold cross-validation was applied to ensure that our system performs high accuracies at stated in (Can et al., 2015). 100% identification accuracy was achieved using kNN, Bayes, decision trees, SVM and NN algorithms (see Table 7). The selected feature (frequency domain peak) was a discriminative feature that can easily differentiate original gold from copper.

6. CONCLUSION

Since gold is one of the most widely counterfeited metals, an automatic counterfeit gold detection system by using the image and sound processing techniques was developed. Manually segmented and original gold and copper images were added as a public dataset for researchers studying in the field of matter segmentation and classification along with the recorded impact sounds. The surface of the metal is investigated with an image processing module, whereas the whole metal is investigated with a sound processing module. Combining sound and image processing modules creates a more robust system against counterfeiting. Bare gram gold and copper can be differentiated by peak frequency of the impact sound with high accuracies. Similarly, bare metals can be segmented and classified easily with image processing techniques. However, there is a different story when the gold or copper inside mika. Sound processing algorithms cannot identify original gold from impact sounds. High-resolution image processing has to be used for this part. Although good accuracies with decision tree algorithm could be achieved (Can et al., 2015), CNNs, Neural Networks and SVM have higher results. With the CNN algorithm, I achieved around 97% accuracy for differentiating precious metals inside mika. The final aim of this research is to create a machine that can deposit gold and withdraw gold automatically, just like ATM machines. Furthermore, jewelers can also use this machine to improve their gold purity prediction accuracy. It is planned to add the density of the matter besides sound and image processing techniques within the scope of our project.

CONFLICT OF INTEREST

The author confirms that there is no known conflict of interest or common interest with any institution/organization or person.

AUTHOR CONTRIBUTION

Yekta Said Can: Designing concepts of the study, application of data analysis and interpretation, implementation of methods and writing the draft of the manuscript.

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