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Artificial Intelligence Based Teta Named Danger Detection and Analysis System

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Abstract:
In this study, an artificial intelligence system was developed to detect dangerous substances. The system functions arduino based and through the sensors. Sensory values were taken both from dangerous and non-dangerous substances. Sensory data were saved to computer environment by the help of arduino and vector machines with artificial intelligence supports were used to detect dangerous and non-dangerous substances with a success rate of 90.33% To secure the classifier 10 layers cross-validation were used. In addition, 500 trials were conducted during the training. A success rate of 90.10% for 10 fold cross-validation was attained at the end of 500 trials. With this work, promising results were obtained in detecting whether or not objects in 1-10 cm range are dangerous or not without the aid of human, by using equipments with a reasonable cost.

Keywords: Danger material, detection, analysis, terror, support vector machines

I. INTRODUCTION

Today, terrorism is gradually increasing. Especially places like shopping centers, public transports, stadiums have a higher potential for such attacks. Explosive substances and pointy metal substances are used commonly in such incidents. The system used in the study has been developed by combining efficient and economic devices with artificial intelligence algorithms in order to detect hazardous materials and to take necessary precautions in time. In world countries like America, United Kingdom, Israel, India and Turkey are conducting studies regarding the matter. With this study, it was aimed to detect the dangerous materials as early as possible without human aid and to minimize the terror incidents. The data to be analysed is obtained through sensors on arduino and transferred to digital environment. Information obtained from the system goes through a pre-process by applying normalization process. The data obtained is then fed to Support Vector Machine trained by Sequential Minimal Optimization algorithm and to detect whether or not the substance is dangerous. A 10 fold cross-validation method was used to ensure the system's detection reliability. The system was run 500 times this way. The average of the results obtained is also included in the study. Our study is structured as follows: studies about this topic are included in the next section. In Chapter 3 the technologies used, data set and the evaluation criteria are explained. Chapter 4, describes the conducted study. In Chapter 5 the experimental results and the discussion section describing the results of the study is given. In section 6 of this document we conclude our article.

II. RELATED WORKS

The most comprehensive study conducted is STANDEX . The studies for STANDEX, conducted by NATO started first in 2010. System was financed by USA, Russia, France, England, ,Italy and Turkey. STANDEX uses a series of sensors and microwave scanning technology. This technology, detects abnormalities in the structure of the molecules. However, STANDEX is said to be the first system to detect masses and scan molecules [1]. SAPER application that was developed in India is among the systems that analyse the explosives in the user's area via a special chip implemented in the smartphone Semwal Bomb detecting chip that was developed by Abhilash Semwal in 2014 is also supported by Microsoft and is financed Indian government for 2 years. Via a magnetometer that measures the magnetic field the app n the smartphone detects the explosive substances. Cloud-based application, when a threat is detected, directly puts forth a warning message and notifies the location to security forces [2]. Radar bomb detector that weighs 5,9 kg and is mounted on a tripod sends radar signals to people and evaluates the polarized signals and detects whether or not a person is threat. This process takes only 1.3 seconds and can be remotely controlled up to 2.7 m. According to the developers of the technology, CBD-100 can choose iron ball bearings, glass, nails, ceramic and stones by choosing metallic and nonmetallic explosives [3]. Counterbomber which is named as suicide bomb detector or detecting system has a design that allows it to be easily installed to different spots. In addition to a camera and detector module mounted on a tripod, the detection system, which has a main unit, is controlled by a laptop computer. This suicide bomb detector that can either be mounted or be used mobile can be used by security forces with ease. A simple report regarding the threat status is transferred to the security personnel after scanning the people entering in angle of camera. The system automatically warns the security personnel when the person being inspected is perceived as carrying a live bomb threat. [4] H.-w. Hübers and colleagues have developed a built-in system with Terahertz (THz) rays to locate hidden bombs and suicide bombers THZ radiation, without harming the humans penetrates into the clothes to detect whether or not there are harmful substances. [5]

III. MATERIAL AND METHOD

The study focuses on a microcontroller. Arduino uno is used as microcontroller. Via arduino uno sensors can exchange data. There are 3 different sensors on the system, including magnetometer, distance and infrared temperature sensor. The

X, Y and Z coordinates, composition and ambient magnetic fields are measured using a magnetometer sensor. Magnetometer value is proportional to the distance to the substance. The distance value to the substance measured using ultrasonic distance sensor HC-SR04. The room temperature and the temperature of the substance are measured using infrared temperature sensor the Grove.

Figure .1. Arduino Used In the System

Arduino is an open source development platform that can interact with its environment in an easy way, that makes it easy for us to program with its libraries, and allows us to read the data from sensors. [6] Arduino that is used is shown in Figure 1.

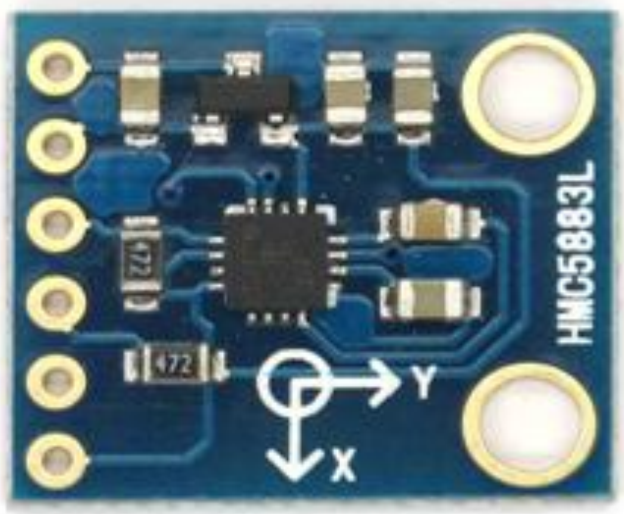

Figure.2. HMC5883L magnetometer sensor used in the system

In the study, 3 different sensor is used including magnetometer, temperature and distance. As seen in Figure 2, HMC5883L magnetometer sensor, is a 3-axis compass sensor which is manufactured by Honeywell. By using the HMC5883L sensor and voltage regulator on this module it can be used comfortably in different systems and in various applications. Thanks to its standard pin structure it can be used in broadboard or different circuits and systems. I ² C digital communication protocol is used in the output of the sensor. Since there is a voltage regulator on the module, a supply voltage of 3-5V can be given. [7]

Figure.3. Grove infrared temperature sensor used in system

Grove infrared temperature sensor is a non-contact temperature measurement model. The black surface of the sensor is good to absorb thermal infrared radiation at the incident that triggers the voltage reaction at the output. This sensor creates an analog voltage based on the temperature (0 ~ 1.1 V). The sensor helps to measure the temperature of the room and the substance. [8]

Figure.4. HC-SR04 ultrasonic distance sensor used in the system

HC-SR04 ultrasonic distance sensor, is a sensor that functions with sound waves that measures from 2 cm to 400 cm with an accuracy up to 3 mm. It is used in reading distance, radar and robot applications [9].

A. *Support Vector Machine (SVM)*

In this study, Support Vector Machine (SVM) was chosen as the classification method. This method is one of the effective methods in machine learning and data mining for pattern recognition. The method was presented in 1995 by Vapnik and Cortes [10]. The method is also a supervised learning algorithm used in regression analysis. This method is a kind of supervised learning algorithm used in regression analysis and classification. The two-class pattern is divided into two different categories by a linear plane. The use of SVM in pattern recognition is described below.

In this algorithm an n-dimensional pattern (object) x has n coordinates, x=(x1, x2, …, xn) where each x is a real number and xi ϵ R for i = 1, 2, …, n and also each pattern xj belongs to a class . Consider a training set T having m number of patterns with their classes, T=[11] and a dot product space S, in which the patterns x are embedded, x1, x2, …, xm ϵ S. A hyperplane in the space S can be written as the following:

$$\{x \in S \mid w \bullet x + b = 0\},\ w \in S, b \in R$$

The dot product $w \bullet x$ is defined by:

$$w \bullet x = \sum_{i=1}^{n} w_i x_i \qquad (1)$$

If there exists at least one linear classifier defined by the pair (w, b) training set of patterns are linearly separable. The classifier correctly classifies all training data as it can be. This classifier is defined by the hyperplane (w•x+b=0) as shown in

Fig.11. Regions for class +1 patterns (w•x+b>0) and for class -1 patterns (w•x+b<0) are defined by this linear classifier.

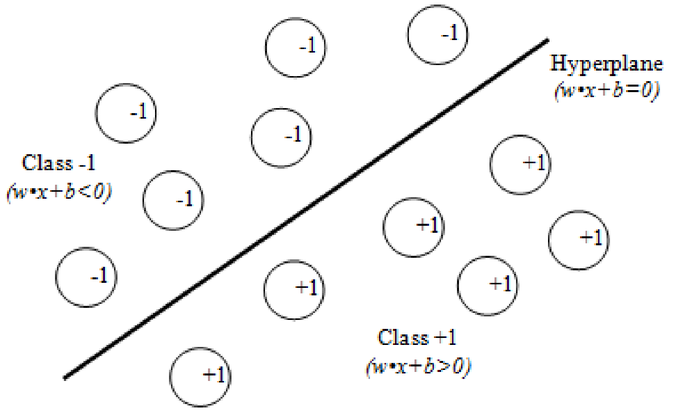

Figure.5. Linear classifier defined by the hyperplane H (w•x+b=0).

The classifier is ready to detect new patterns after being trained. New patterns to be identified, are different from those used for training. The xk pattern class is specified as follows:

$$class\left(x_k\right)=\begin{cases}+1 \ if \ \ w\cdot x_k+b>0\\ -1 \ if \ \ w\cdot x_k+b<0\end{cases} \qquad (2)$$

Classification of new patterns are only depended to the sign of the (w•x+b) expression [12].

Sequential Minimal Optimization (SMO) Algorithm

Sequential minimum optimization (SMO) algorithm is widely used in training support vector machine (SVM). Equation 5 shows the presentation of a SVM primal optimization problem.

$$\max_{\alpha} \Psi(\alpha)=\sum_{i=1}^{N}\alpha_i-\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}y_i y_j k(x_i,x_j)\alpha_i\alpha_j$$

$$\text{subject to } \sum_{i=1}^{N}y_i\alpha_i=0,\ 0\le\alpha_i\le C,\ \ and \ \ i=1,\ldots,n \qquad (3)$$

Where xi is a training sample, yi є {-1,+1} is the corresponding target value, αi is the Lagrange multiplier, and C is a real value cost parameter. Detailed information and explanations about this subject are given in the study of Kuan T. W. et al [13]

Performance evaluation

Performance evaluation and validation methods used in the system are confusion matrix, classification accuracy, analysis of specificity and sensitivity, and k-fold cross-validation. Mathematical formulas of performance evaluations are explained in the following sections. [14, 15]

Classification accuracy

The equation given in formula 4 is used to measure the accuracy of the classification of data used in the study.

$$accuracy(T)=\frac{\sum_{i=1}^{N}assess(t_i)}{N},\quad t_i\in T \qquad (4)$$

$$assess(t_i)=\begin{cases}1, \ if \ \ classify(t_i) \ \equiv correctclassication,\\ 0, \ \ otherwise,\end{cases} \qquad (5)$$

Where T is the set of data items to be classified (the test set) and N is the number of testing samples of the data-set. In this method, experimental studies show that the optimum value for k is ten [16, 17]. Also the accuracy of performed 10-fold cross-validation (CV) experiment will be shown.

Confusion matrix

In the field of machine learning, a confusion matrix is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one[18]. The confusion matrix contains four classification performance indices: true positive, false positive, false negative, and true negative as shown in Table 1. These four indices are also usually used to evaluate the performance the two-class classification problem [19].

Table.1.The four classification performance indices included in the confusion matrix

Actual class	Predicted class	
	Positive	Negative
Positive	True positive (TP)	False negative (FN)
Negative	False positive(FP)	True negative (TN)

True negative is the number of correct predictions that an instance is negative. False positive is the number of incorrect predictions that an instance is positive. False negative is the number of incorrect predictions that an instance is negative, and True positive is the number of correct predictions that an instance is positive [11].

Analysis of sensitivity and specificity

For sensitivity, specificity, positive predictive value and negative predictive value, we use the following expressions [11].

$$Sensitivity(\%)=\frac{TP}{TP+FN}\times 100 \qquad (6)$$

$$Specificity(\%)=\frac{TN}{TN+FP}\times 100 \qquad (7)$$

$$Positive\ predictive\ value(\%)=\frac{TP}{TP+FP}\times 100 \qquad (8)$$

$$Negative\ predictive\ value(\%)=\frac{TN}{TN+FN}\times 100 \qquad (9)$$

True positive (TP): An input is detected as a patient with atherosclerosis diagnosed by the expert clinicians.

True negative (TN): An input is detected as normal that is labeled as a healthy person by the expert clinicians.

False positive (FP): An input is detected as a patient that is labeled as a healthy by the expert clinicians.

False negative (FN): An input is detected as normal with atherosclerosis diagnosed by the expert clinicians [11] .

K-fold Cross-Validation

The k-fold cross-validation is used to make the result of the classification tests more reliable [20] . In this validation, the data is randomly divided into k sub-samples. One of the K sub-examples is maintained as verification data to test the model. The remaining k-1 sub-samples are used as training data. K cross-validation is repeated with each of the k sub-samples at least once as test data[21]. According to the results obtained from experimental studies in cross-validation processes used in classification, the most optimal k value is ten. [16, 17]. For this reason, a k-value of 10 was taken for cross-validation in the study.

DATASET

8 parameters are taken which are X, Y and Z coordinates, the resultant and the ambient magnetic fields, room temperature, substance temperature, distance to the substance. The data that were attained from the non-dangerous object which the book are shown in table 2, and the data attained from dangerous object which is the knife is shown in Table 3. The range of values for the data set created from dangerous and non-dangerous objects is shown in Table 4.

Table. 2. Sensor readings are taken from the book object

MAGNETOMETER SENSOR					DISTANCE SENSOR	TEMPERATURE SENSOR	
X	Y	Z	Resultant	Environment Magnetic Field	Distance	Substance Temperature	Room temperature
31.74	28.06	-8.74	43.26	43.48	2.94	29.13	27.40
31.83	28.15	-8.56	43.35	43.48	03.02	29.07	27.40
31.65	28.34	-8.83	43.39	43.48	03.09	29.11	27.49
31.83	28.24	-8.83	43.46	43.48	2.37	29.12	27.44
31.65	28.15	-8.92	43.29	43.48	2.73	28.97	27.30
31.92	28.15	-8.92	43.49	43.48	3.87	29.08	27.17
31.83	28.34	-8.83	43.52	43.48	2.68	29.41	27.44
31.65	28.06	-8.65	43.17	43.48	2.68	29.51	27.40
31.74	28.15	-8.83	43.34	43.48	2.73	29.56	27.44
31.92	28.24	-8.83	43.53	43.48	2.73	29.41	27.44

Table.3. Sensor values obtained from the Knife object

MAGNETOMETER SENSOR					DISTANCE SENSOR	TEMPERATURE SENSOR	
X	Y	Z	Resultant	Environment Magnetic Field	Distance	Substance Temperature	Room temperature
75.53	76.54	-2.67	107.57	48.49	2.94	35.17	27.08
75.62	76.45	-2.48	107.56	48.49	2.99	34.72	26.69
77.00	79.49	1.38	110.68	48.49	2.99	34.83	26.80
77.46	82.71	5.89	113.47	48.49	2.99	34.68	26.73
77.74	83.17	6.99	114.06	48.49	2.89	34.96	27.08
78.02	83.54	7.73	114.56	48.49	2.99	34.90	26.87
77.28	83.81	8.83	114.34	48.49	2.99	34.60	26.80
76.18	84.92	12.05	114.71	48.49	2.99	34.71	26.73
75.99	85.19	12.33	114.82	48.49	2.87	34.93	27.27
76.08	85.47	11.96	115.05	48.49	2.99	34.68	26.82

Table .4. The mean values of the data set obtained

Feature	MAGNETOMETER SENSOR				DISTANCE SENSOR		TEMPERATURE SENSOR	
	X	Y	Z	Resultant	Environment Magnetic Field	Distance	Substance Temperature	Room temperature
AVG	24,35	31,65	-22,63	68,22	31,95	4,27	45,96	27,19
Max	185,47	184,46	182,9	652,69	43,09	9,66	48,49	28,14
Min	-376,83	-376,83	-376,83	10	21,38	0	41,43	26,42
Std Dev	61,39	31,27	67,02	81,79	3,68	1,15	1,84	0,31

In the data set, a total of 9363 data were used, with 4694 harmful substances and 4669 harmless substances.

IV. DEVELOPED SYSTEM

Each substance has a unique electromagnetic wave. It is aimed to use these waves in detection methods. In this study, temperature and magnetic field properties of the substance was used. Magnetometer is a tool used to measure the magnetic field intensity. The magnetometer operates according to the iron ore ratio in the environment. One of the important uses of magnetometers is to measure the magnetic field of our earth. Magnetometer can detect where underground metal sources like iron, copper ore are by using the irregularity of magnetic field. One of the areas that we encounter magnetometers in daily life is security. It is scanned whether or not there are metals like guns on people who enters crowded areas such as airports, police checkpoints, shopping centers. If there is a magnetic object on the people entering through the checkpoint, the magnetic field will be distorted and an alarm will sound when the deterioration is detected. With the working principle of magnetometry, treasure hunters can find precious ores hidden underground. A mine detector is an example of a magnetometer that can be used to find mines hidden underground. Magnetometer and infrared temperature sensors are used to obtain distance and room temperature values of substances. Data set was generated from the values obtained from dangerous and non-dangerous substances. Objects that belong to the sample images is shown in Figure 6 and 7.

Figure .6. pictures of harmful substances tried in the system

Figure.7. images of objects tried in the system

Decision support system was created by using support vector machines with the data in the generated data set. In the system we divide the data into 10 equal parts. We used 9 parts for training. The support vector machines that we use as classifiers have trained themselves according to this. It is then asked to estimate, according to the training, the other data which we have not given the result of classification for. Estimates obtained by the classifier are compared with actual results. We divide the correct guess to all the data and multiply by 100 to find the accuracy percentage of the classification. The system was run 10 times in total so that each part was tested at least once. All obtained accuracy rates were summed and divided by 10 to find the average accuracy rate.

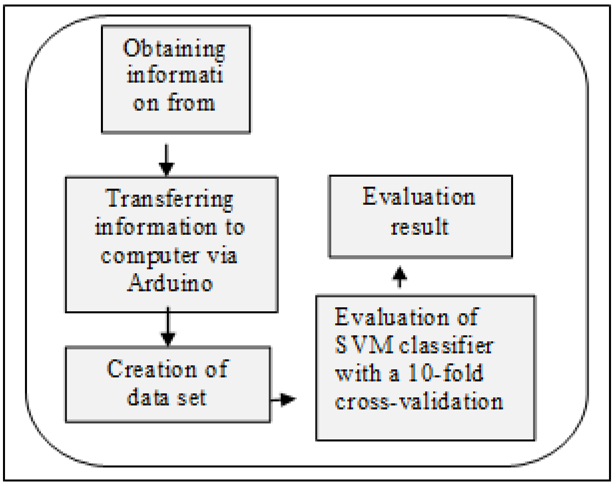

Figure.8. Diagrams of the operations in Table 5 are given.

Classification parameters

In this study, a system based on the SVM classification algorithm was developed to determine whether or not substances at a certain distance are harmful. The credibility of this classifier is provided by the k-fold cross-validation method. When this classifier was used, training was carried out according to the parameters given in Table 6.

Table .6. List of classification parameters

Parameters	Value
Method	SVM
Optimization algorithm	SMO
Validation method	k-fold cross-validation (10-fold CV)
Kernel Function	Linear
Toolkit	1.0000e-003
MaxIter	15000
Kernel Cache Limit	5000
The initial value	Random

V. EXPERIMENTAL RESULTS AND DISCUSSION

Table.7. Classification performance for the dataset obtained from the sensors on the Arduino

Performance Criterians	SVM
Correct Classification Rate (%) (500 process)	90.10
Correct Classification Rate (%)	90.30
Sensitivity (%)	91.56
Specificity (%)	89.07
Positive predictive value (%)	89.29
Negative predictive value (%)	91.39
Elapsed time (seconds)	82.70

As shown in Table 7, the determinations of harmful and non-harmful substances in the data set formed by the information obtained from the sensors on the arduino were determined by classification with support vector machine. 10-fold cross-validation was used to increase the security of the classification. In this way, the system was operated 500 times and the correct detection rate of the items was determined as 90.10% on average. In these runs, the highest accuracy rate with 10-fold cross-validation was found to be 90.30%. As can be seen from the ratios, it can be seen that the system will allow the operators to separate the harmful substances more effectively.

VI. CONCLUSIONS

In this study, it is intended to detect dangerous substances in such places as airport entrances, shopping centers without the need for human by using of artificial intelligence algorithms. With the conducted study detection of dangerous substances were achieved with a high rate of success. With the developed model, studies on dangerous and non-dangerous substances were carried out and successful results were obtained. Properties of magnetic field, temperature and distance were used to make the detection. With this study, dangerous substances will be detected and intervened and terrorist early by the security forces and terror incidents will be reduced. Decision support system was made with Support Vector Machine classifier in the study. The developed system had 90.30% accuracy. With the methods used, the results obtained were quite successful and the model looks quite promising for the recognition applications. By adding remote sensors to the system,dangerous items will be detected from a distance such as live bombs, weapons, knives, bombs and so on. With these additions, it is aimed to intervene the events earlier.

VII. REFERENCES

[1].Chirico, R., et al., Proximal detection of traces of energetic materials with an eye-safe UV Raman prototype developed for civil applications. Sensors, 2015. 16(1): p. 8.

[2].Photiou, S., CBRNE-Terrorism Newsletter–2012©.

[3].ALBUQUERQUE, N.M. Suicide bomb detector moves forward with Sandia engineer's help. 2016; Available from: https://share-ng.sandia.gov/news/resources/news_ releases/ bomb _detector/#.WyVejqf-hPa.

[4].Rapiscan. 2018; Available from: http://itt-kubba. com/ products/ Rapiscan/Counterb/CounterBomber.pdf.

[5].Hübers, H.-W., et al. Terahertz imaging system for stand-off detection of threats. in Terahertz for Military and Security Applications V. 2007. International Society for Optics and Photonics.

[6].Badamasi, Y.A. The working principle of an Arduino. in Electronics, computer and computation (icecco), 2014 11th international conference on. 2014. IEEE.

[7].Brzozowski, B., et al. A concept of UAV indoor navigation system based on magnetic field measurements. in Metrology for Aerospace (MetroAeroSpace), 2016 IEEE. 2016. IEEE.

[8].wikipedia. 2018; Available from: http://wiki.seeed.cc/ Grove- Infrared_Temperature_Sensor/.

[9].Madli, R., et al., Automatic detection and notification of potholes and humps on roads to aid drivers. IEEE sensors journal, 2015. 15(8): p. 4313-4318.

[10].Cortes, C. and V. Vapnik, Support-Vector Networks. Machine Learning, 1995. 20(3): p. 273-297.

[11].Polat, K. and S. Gunes, Breast cancer diagnosis using least square support vector machine. Digital Signal Processing, 2007. 17(4): p. 694-701.

[12].Ivanciuc, O., Reviews in Computational Chemistry. Vol. 23. 2007: John Wiley & Sons, Inc. 291-400.

[13].Kuan, T.W., et al., VLSI Design of an SVM Learning Core on Sequential Minimal Optimization Algorithm. Ieee Transactions on Very Large Scale Integration (Vlsi) Systems, 2012. 20(4): p. 673-683.

[14].Yilmaz, N., O. Inan, and M.S. Uzer, A New Data Preparation Method Based on Clustering Algorithms for Diagnosis Systems of Heart and Diabetes Diseases. Journal of Medical Systems, 2014. 38(5).

[15].Polat, K. and S. Gunes, Hepatitis disease diagnosis using a new hybrid system based on feature selection (FS) and artificial immune recognition system with fuzzy resource allocation. Digital Signal Processing, 2006. 16(6): p. 889-901.

[16].Breiman, L., et al., Classification and regression trees. 1984: Wadsworth & Boks / Cole Advanced Boks & Software.

[17].Kohavi, R., A study of cross validation and bootstrap for accuracy estimation and model selection, in The Fourteenth International Joint Conference on Artificial Intelligence. 1995: San Francisco. p. 1137-45.

[18].Stehman, S.V., Selecting and interpreting measures of thematic classification accuracy. Remote Sensing of Environment, 1997. 62(1): p. 77-89.

[19].Xu, Y., Q. Zhu, and J.H. Wang, Breast cancer diagnosis based on a kernel orthogonal transform. Neural Computing & Applications, 2012. 21(8): p. 1865-1870.

[20].Francois, D., et al., Resampling methods for parameter-free and robust feature selection with mutual information. Neurocomputing 2007. 70: p. 1276-1288.

[21].Diamantidis, N.A., D. Karlis, and E.A. Giakoumakis, Unsupervised stratification of cross-validation for accuracy estimation. Artificial Intelligence 2000. 116 p. 1-16.