

# DETECTION AND CLASSIFICATION OF CANCER CELLS USING BRAIN AND BREAST MRI IMAGES

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**Abstract** – The accurate and automated classification is very much important using the MRI brain and breast images for medical analysis, including its primary site, is important for better understanding of cancer. The big data of somatic gene mutations provides a great opportunity to investigate cancer classification using machine learning. In this paper, the method for classifying the given MRI brain and breast image as benign or malignant is proposed. The proposed method first employed discrete wavelet transform to extract features from images, followed by applying Grayscale image and Gaussian Filter image to reduce the noise and to blur the image. The reduced images were send for classification using kernel support vector machine (KSVM). We have used Fitckernel method for classification. The strategy of K-fold stratified cross validation was used to enhance generalization of KSVM, Confusion matrix plot used for accuracy calculation. Expected outcome of this research is that more accurate result will be generated for Detection and Classification of brain and breast cancer cells in MRI Images.

**Keywords-** Brain, Breast, MRI, Kernel Support Vector Machine, Fit Gaussian Kernel.

## 1. INTRODUCTION

Magnetic resonance imaging (MRI) is an imaging technique used in radiology in which it gives us the images of the anatomy of the body. They use magnetic fields and radio waves to get the clear image of the body parts which helps us in clinical analysis. Using those MRI images of brain and breast, doctors can able to verify if a tumor is or is not a cancer. MRI images can also shows us from when it started to spread and from where it started to spread through the whole body. MRI images can also be able to help doctors to plan the treatment whether it is a surgery or radiation therapy. Cancer can be formed at any place in the body. Cancer starts when the normal cells starts to mutate. Most of the people, had been treated successfully from the cancer. There are lots of cancer types that is colon, lungs,

breast, even though in blood. Cancers can be same like in most of the ways, but the way they grow and spread varies according to the patient's condition. Some may grow and spread so soon, others may grow slow. Some cancer types are well treated and cured with the help of surgery, some cancers is cured using drugs (chemotherapy). Often more than one is getting good results in the treatment. Most of the cancers form a growth (i.e) tumor. But all the tumor cells are not considered as cancer. Doctors will test the tumor cells and find out whether it is a cancer.

- A Tumor which doesn't contains cancer cells are called benign
- A Tumor which contains cancer cells are called malignant

In most of the cancers, like leukemia, the tumors will not be developed. They grow in various parts in the cells of the body. Because cancer belongs to complex type of diseases, it can be developed from various sources such as lifestyle, genetics, products and environmental factors. The cancer consists of many stages (i.e) The starting stage (1 or 2) which means the cancer has not yet started to spread. The final stage

## 1.1 Background

Breast cancer is the one of the most founded case in the world of women. It is 25% out of 100% among all cases of cancer founded, and 2.1 Million people had been affected through this. The cancer starts when the cells from the breast begin to mutate fast and out of control. These cells usually form tumors which could be able to see via MRI, Mammogram or seems as tumor in the breast part. Chances of survival increases by early diagnosis significantly. The challenges in it is detecting it and classifying a tumors as malignant (cancerous) or benign (non-cancerous). A tumor is said to be malignant when the cells grow around the tissues or spreads to various areas in the body. A tumor in benign will not spread to other parts of the body the way the malignant tumors does. But tumors in benign can be dangerous if they started to

spread when we are not aware. Machine Learning helps in detecting the tumor in breast cancer as well as in all cancers. Research tells us that the experienced physicians able to identify the cancer by 79% accuracy, where the 91% (or up to 97%) accuracy can be achieved from the Machine Learning techniques.

The abnormal diseased cells in the brain is formed as brain tumor. The skull, that encloses the brain, is very strong. Growth of tumor inside a restricted space like this can cause risk. Brain tumors can also be normal (malignant) or abnormal (benign). Even when there is benign or malignant tumors growth, they may cause the pressure inside the skull which increases the risk. This causes severe risks like brain damage. Brain tumors are segregated as primary or secondary. The primary tumors are said to be benign. A secondary tumor, which is also known as a metastatic brain tumor, that occurs when cancer formed cells spread to the brain from other part of the organ, that is the lung or breast. Compared to other tumors brain tumors are mostly found in children and aged adults, even though people from any age can get a brain tumor. Various types of brain tumors, like “meningioma”, are more common in women.

### 1.2 Objective

The main scope of this project is to identify whether there is any possibilities and stages of cancer. In this project we are going to identify whether the possibility and stages of the cancer and we are going to identify the cancer for two cancers such as brain and breast using the data which is being trained, family history and gene mutation once after some symptoms like stools discharge color which is very early stage of cancer. So that we are able to know the primary site of cancer for early detection and treatment.

### 1.3 Benefits of the project

The benefits of this project is that by using this project we can able to identify the cancer in the early stage by knowing the primary site for both brain and breast cancer, by using the data which is trained and also by using the family history and gene mutation and some symptoms like stool discharge color and pain which is the early symptom of cancer and also the accuracy for overall data will be displayed. So that we can able to identify the primary site and treat the cancer.

### 1.4 Proposed System

In proposed system we are going to denote whether there is possible and stages of cancer. It identifies the primary site of the cancer and the stage using the datasets which is being trained and tested and also family history, gene mutation and some symptoms like difference in stool discharge color and pain. The project is implemented

using MATLAB. We are going to detect and classify the cancer cells for brain and breast cancer.

### ADVANTAGES OF PROPOSED SYSTEM

1. The software is going to identify whether there is possibilities and stage of cancer in the input using which is trained from the MRI images and condition of the patient.
2. It provides the possibilities of cancer in input image for two cancers such as brain and breast in the format of benign and malignant and also the accuracy in percentage for overall data.

## 2. SYSTEM MODEL

### 2.1 Preprocessing

- Our method contains three stages:
1. Preprocessing technique (i.e) feature extraction and feature reduction.
  2. Training the data using the KSVM algorithm.
  3. Predicting the results and accuracy.

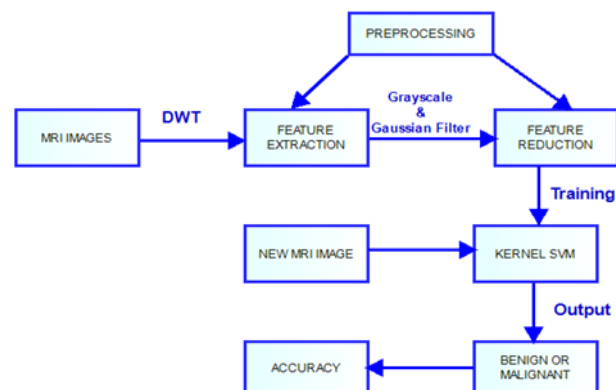


Fig -1: Methodology of Proposed Algorithm

### 2.2 Feature Extraction

Fourier transform-FT is used as a specified tool for the signal analysis, constituent sinusoids of different frequencies is broken down from time domain signal, thus frequency domain which transforms the signal from time domain. However, discarding the time information of the signal is a serious drawback in FT. Thus, as the time information is lost the quality of the classification decreases. To analyze only a small section of the signal at a time Gabor has adapted the FT method. This technique is called short time Fourier transform (STFT) or windowing. The window of particular shape is added to the signal. The time information and frequency information can be compromised from STFT. It provides various information about the frequency and time domain. Where the information is limited in the size of the window. The logical step is represented by Wavelet transform (WT): A

method called windowing containing variable size. Where both time and frequency information of the signal is preserved. The different way to view data is a time-scale technique, but it is considered as a powerful and natural way, because, “scale” is commonly used in daily life compared to “frequency”. Meanwhile, Compared to high or low frequency, the large or small scale is easily understood.

### 2.3 Discrete Wavelet Transform

The dyadic scales and positions is used in the implementation of WT using the discrete wavelet transform [16]. The fundamentals of DWT are as follows

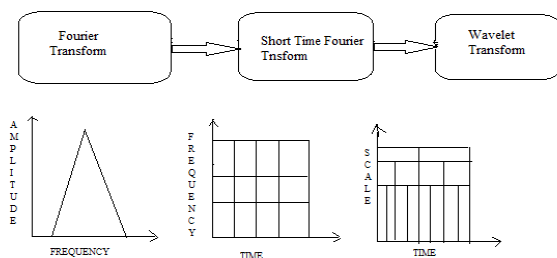


Fig -2: The formation of signal analysis.

Square-integrable function- $x(t)$ , then wavelet  $\psi(t)$  relative to the continuous wavelet transform of  $x(t)$  is defined as, Eq-1

$$W_{\psi}(s,y) = \int_{-\infty}^{\infty} x(t)\Psi_{s,y}(t)dt$$

Where, Eq-2

$$\Psi_{s,y}(t) = 1/\sqrt{s}(\Psi)(t-s/y)$$

Where, from the wavelet  $\psi(t)$  and the wavelet  $\Psi_{s,y}(t)$  is calculated by dilation and translation:  $y$ -translation parameter (both real positive numbers) and  $s$  - dilation factor. Throughout the development of wavelet analysis they have gained popularity from several different kinds of wavelets. Harr is the most important wavelet, where it is the simple one and often in a lot of applications the wavelet is preferred [17-18].

By restraining  $a$  and  $b$  Eq-1 can be discretized to ( $a = 2b$  &  $a > 0$ ) a discrete lattice to give the DWT, which is expressed as. Eq-3

$$cs_{j,k}(n) = DS[\sum_n x(n)l_i^*(n-2^j k)]$$

$$cy_{j,k}(n) = DS[\sum_n x(n)m_j^*(n-2^j k)]$$

Where  $cy_{j,k}$  &  $cs_{j,k}$  are the coefficients of the detail components and the approximation components, respectively.  $l(n)$ -the low-pass filter and  $m(n)$ -high-pass filter, respectively.  $j$  - the wavelet scale and  $k$  - translation factors, respectively. Operator DS-downsampling. The fundamental of wavelet decomposes is represented in Eq-

3. It involves in decomposing the signal  $[x(n)]$  into two form of signals,  $ca(n)$ -approximation coefficients and  $cd(n)$ -detail components. This formation is said as one-level decompose. With successive approximations the above decomposition process can be iterated which in turn being decomposed, in which that one signal has been broken down into different resolution levels. This full process is said to be called wavelet decomposition tree.

### 2.4 Feature Reduction

Storage memory and computation times increases from the excessive features. Whereas, sometimes they make the classification as complicated one, which is now said as the curse of dimensionality. It is said that the number of features are required to be reduced.

#### GRAYSCALE IMAGE

The Grayscale is said as the monochromatic shades from black to white. Where, no other colors are presented in this image only the shades of gray is presented. While grayscale or black and white images can be saved from digital images, even grayscale information is contained in color images. This is to say that the luminance value is presented in each pixel, regardless of its color. Luminance is said as intensity or brightness, which is said to be measured from black with 0 intensity to white with full intensity on a scale. A minimum of 8-bit grayscale is supported in most image file formats, in which it provides 256 levels of luminance per pixel or  $(2)^8$ . Grayscale of 16-bit are supported in few formats, that provides luminance of 65,536 levels or  $(2)^{16}$ . Most of programs related to image editing allows us to convert into black and white, or grayscale from a color image. The process involves in removing all the colour related information, by leaving the pixels luminance. Using a combination of the blue (RGB), red and green colors digital images are displayed, each pixel contains three different luminance values. Therefore, when the colour is removed from an image where a single value is combined from these three values. First all the luminance values for the pixel has to be averaged. Second one is from the blue, red, or green channel keeping only the luminance values. Other custom grayscale conversion algorithms is provided by some programs that allow us to generate a black and white image with the appearance that we would like to prefer.

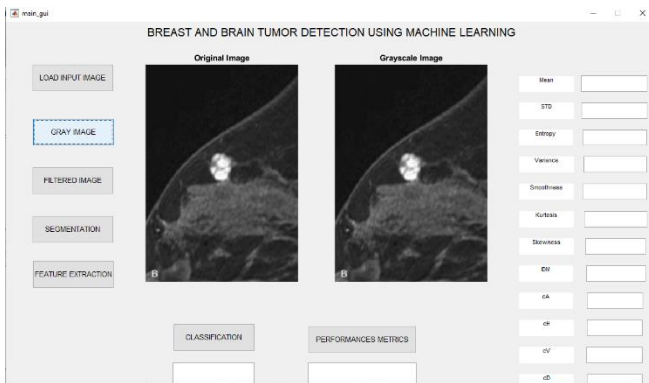


Fig -3: Grayscale Image Conversion

### GAUSSIAN FILTER IMAGE

A Gaussian filter image is said to be called as linear filter. It is used in reducing the noise of the data and blur the data. We can use them to “un-sharp masking” that is edge detection, If we use two of them and by subtracting. The Gaussian filter method can only be used to blur the edges and deduce the contrast of the image. For reducing noise of the image the most commonly used Gaussian smoothing filters is used. Gaussian filtering are usually said to be isotropic, (i.e) along both the dimensions they had the same standard deviation method.

By using an “isotropic Gaussian filter” method in which by using a scalar of the value instead of sigma the image is filtered. In image processing method, Gaussian smoothing also known as a Gaussian blur, by using a Gaussian function named by a scientist Carl Friedrich Gauss an image is resulted in blurring. In graphics software it is a widely used method, especially to reduce the image details and the noise.

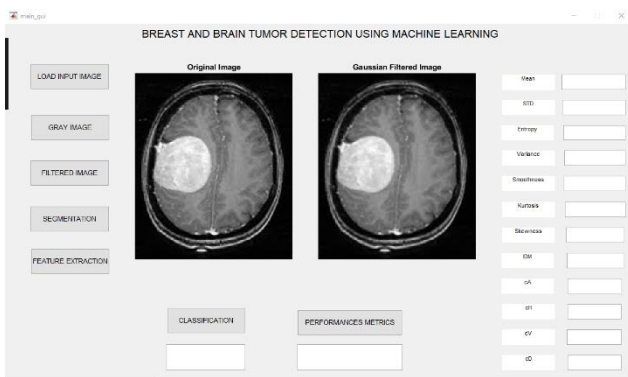


Fig -4: Gaussian Filter Image Conversion.

## 3. CLASSIFICATION

### 3.1 Kernel SVM

In the field of machine learning the support vector machine (SVM) is a landmark. The advantages of SVMs include high accuracy, elegant mathematical tractability, and direct geometric interpretation [20]. Recently, more types of improved SVMs had been grown in a rapid range,

in which the KSVMs-kernel SVM is the most effective and popular one. Kernel SVMs have the following advantages [21]:

- 1) Work much in practice and had a success as computer vision, bioinformatics, natural language categorization in the diverse fields.
- 2) Tunable parameters.
- 3) Convex quadratic optimization is involved in the training [22]. Therefore, the solutions are usually unique and global, thus by avoiding the other statistical learning systems like neural networks is exhibited from convergence to local minima.

### 3.2 Fitckernel Principle's

For classifying the nonlinear data a binary GK classification model is trained and cross-validated using the Fitckernel function. The applications of big data which has large number of training sets but can be able to apply even smaller data sets that can able to be fit in memory using the fitckernel function. Fitckernel function and also be able to plot data which is in the low-dimensional area into a high-dimensional area, after that by minimizing the regularized objective function it involves in fitting a linear model which in the high-dimensional space. By applying the Gaussian kernel to the model in the low-dimensional space we can be able to obtain the linear model in the high-dimensional space which is equal. The linear classification models contains the logistic regression models and regularized SVM.

$$\text{Eq-4: } \text{training} = \text{fitckernel}(a,b);$$

Eq-4: gives the binary GK model of the classification which is trained in by using (X- predictor data) and (Y- corresponding class labels). The predictors in a low-dimensional space is plotted with the high-dimensional space using the fitckernel function, then the transformed predictors and class labels is fitted in a binary SVM model. In the low-dimensional space the Gaussian kernel classification model is equivalent to the linear model.

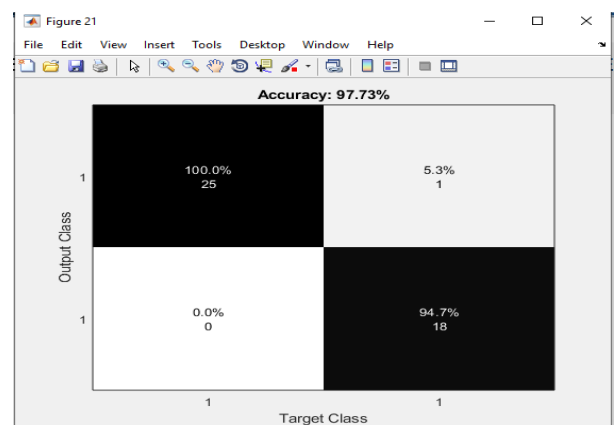


Fig -5: Confusion Matrix Plot

In [Fig 3] the test-set labels are predicted, for the test set it constructs a confusion matrix plot, and for the test set it estimates the classification error.

### 3.3 Radial Basis Function (RBF)

For finding a regression line or non-linear classifier using the machine learning the function called RBF is used. The transformation of n-dimensional input to m-dimensional input is done using the kernel functions, in which  $m > n$  then in higher dimensional we need to find the dot efficiently. The main purpose to use the kernel function is: Higher dimensions which contains a linear classifier or regression curve becomes a lower dimensions which contains a Non-linear classifier or regression curve. The formula Definition of RBF:

$$K(a,b) = \exp(-||a-b||^2 / 2\sigma^2)$$

In which  $(a, b)$ -vector point in dimensional space. the exponential expression of  $(a, b)$  is  $e^x$ .

### 3.4 Polynomial Kernel

The polynomial function is usually used in the SVM that is in the machine learning and other kernel related models, which represents the vectors which are seen to be similar that is the training samples which are in a feature space over polynomials which contains the originality of variables, of non-linear models which is allowing for learning. Formula Definition of PK:

$$K(a_i, b_j) = (a_i \cdot b_j + 1)^d$$

### 3.5 Accuracy Findings

In my highest findings the accuracy is calculated as overall data for Brain and Breast MRI images which is trained and tested using the kernel functions is 97.73%. The accuracy calculation of the data for brain and breast cancer is:

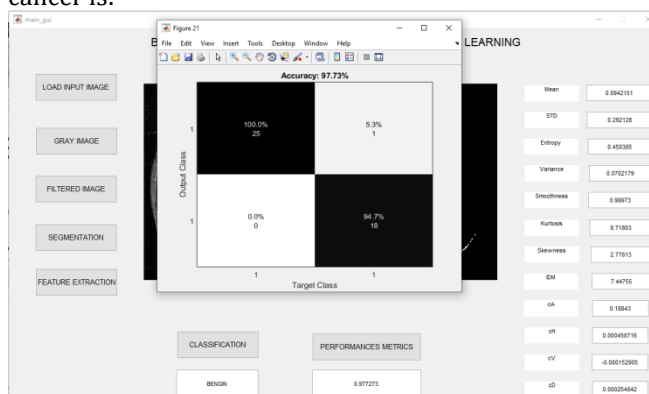


Fig -6: Accuracy Findings

## 4. CONCLUSION

In this study, we have developed a novel "DWT + GF + FitkSVM" method to distinguish between normal and abnormal MRIs of the brain and breast. In this paper, the performance of the proposed algorithm obtained better

compared with the conventional schemes. In detecting human brain and breast tumor, the sensitivity of the proposed algorithm is 96.15% for brain and breast MRI images. In addition, the specificity of the proposed algorithm is 100% for brain and breast MRI images. Moreover, the overall accuracy of the proposed algorithm for brain and breast MRI images is 97.73%. However, the time required to detect brain and breast tumor with the proposed algorithm is very short than conventional algorithms.

## REFERENCES

- [1] "Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM", Nilesh Bhaskarrao Bahadure, Hindawi International Journal of Biomedical Imaging Volume, 2017.
- [2] "An Brain images classifier via PCA and KSVM" Y.Zhang \*and L. Wu, Progress in Electromagnetics Research, 2017.
- [3] "Feature Selection and Classification of Breast Cancer on Dynamic Magnetic Resonance Imaging by Using Artificial Neural Network, IEEE
- [4] "Brain Tumor Detection and Classification with Feed Forward Back-Prop Neural Network." arXiv preprint arXiv: 1706.06411, 2017.
- [5] "Detection and Classification of Brain Tumor using Machine Learning Approaches", BR Pushpa, International Journal of Research in Pharmaceutical Sciences, 2019.
- [6] "Detection and classification of cancer from microscopic biopsy images using clinically significant and biologically interpretable features", Ying Zhuge, volume, 2015.
- [7] "Accurate Classification and Detection of Brain Cancer Cells in MRI and CT Images using Nano Contrast Agents", Journal (BPJ), 2016.
- [8] "Pham N. H. Tra, Nguyen T. Hai, Tran T Mai," Image Segmentation for Detection of Benign and Malignant Tumors", 2016 International Conference on Biomedical Engineering (BME-HUST), 2016.
- [9] "Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines", 42<sup>nd</sup> International Conference on TSP, 2019, IEEE.
- [10] "Brain Tumor Detection Using Anisotropic Filtering, SVM Classifier and Morphological Operation from MR Images", 2018(IC4ME2), IEEE.

- [11] "Brain tumor classification and segmentation in MRI images using PNN", 2017 IEEE Conference on ICEICE, 10.1109/ICEICE.2017.8191888, IEEE.
- [12] "Segmentation and 3D reconstruction of MRI images for breast cancer detection", International Image Processing, Applications and Systems Conference, 2014, IEEE.
- [13] "Deep Learning Assisted Efficient AdaBoost Algorithm for Breast Cancer Detection and Early Diagnosis", Deep Learning Algorithms for Internet of Medical Things, 2020, IEEE.
- [14] "An Approach for the Detection and Classification of Tumor Cells from Bone MRI Using Wavelet Transform and KNN Classifier", 2018 International Conference on ICIET, IEEE.
- [15] "Brain tumor detection based on Naïve Bayes Classification", 5<sup>th</sup> International Conference on ICEAST, Hein Tun Zaw, 2019, IEEE.
- [16] "Automated Detection of Brain Tumor Cells Using Support Vector Machine", 9<sup>th</sup> International Conference on ICCNT, Geetanjali Birare, 2018, IEEE.
- [17] Zhang, Y. and L. Wu, "Crop classification by forward neural network with adaptive chaotic particle swarm optimization," *Sensors*, Vol. 11, No. 5, 4721–4743, 2011.
- [18] Zhang, Y., S. Wang, and L. Wu, "A novel method for magnetic resonance brain image classification based on adaptive chaotic PSO," *Progress In Electromagnetics Research*, Vol. 109, 325–343, 2010.
- [19] Ala, G., E. Francomano, and F. Viola, "A wavelet operator on the interval in solving Maxwell's equations," *Progress In Electromagnetics Research Letters*, Vol. 27, 133–140, 2011.
- [20] Iqbal, A. and V. Jeoti, "A novel wavelet-Galerkin method for modeling radio wave propagation in tropospheric ducts," *Progress In Electromagnetics Research B*, Vol. 36, 35–52, 2012.
- [21] Martiskainen, P., et al., "Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines," *Applied Animal Behaviour Science*, Vol. 119, Nos. 1–2, 32–38, 2009.
- [22] Bermejo, S., B. Monegal, and J. Cabestany, "Fish age categorization from otolith images using multi-class support vector machines," *Fisheries Research*, Vol. 84, No. 2, 247–253, 2007.
- [23] Muniz, A. M. S., et al., "Comparison among probabilistic neural network, support vector machine and logistic regression for evaluating the effect of subthalamic stimulation in Parkinson disease on ground reaction force during gait," *Journal of Biomechanics*, Vol. 43, No. 4, 720–726, 2010.
- [24] Bishop, C. M., *Pattern Recognition and Machine Learning (Information Science and Statistics)*, Springer-Verlag New York, Inc., 2006.
- [25] Vapnik, V., *The Nature of Statistical Learning Theory*, Springer-Verlag New York, Inc., 1995.
- [26] Jeyakumar, V., J. H. Wang, and G. Li, "Lagrange multiplier characterizations of robust best approximations under constraint data uncertainty," *Journal of Mathematical Analysis and Applications*, Vol. 393, No. 1, 285–297, 2012.
- [27] Cucker, F. and S. Smale, "On the mathematical foundations of learning," *Bulletin of the American Mathematical Society*, Vol. 39, 1–49, 2002.
- [28] Poggio, T. and S. Smale, "The mathematics of learning: Dealing with data," *Notices of the American Mathematical Society (AMS)*, Vol. 50, No. 5, 537–544, 2003.
- [29] Acevedo-Rodríguez, J., et al., "Computational load reduction in decision functions using support vector machines," *Signal Processing*, Vol. 89, No. 10, 2066–2071, 2009.
- [30] Deris, A. M., A. M. Zain, and R. Sallehuddin, "Overview of support vector machine in modeling machining performances," *Procedia Engineering*, Vol. 24, 308–312, 2011.