ISSN:0975-9646

Mayur Rahul/ (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 7 (3) , 2016, 1220-1224

A Robust Approach for Detection of Brain Anomalies using MRI

Mayur Rahul[#1]

[#]UIET, CSJMU, Kanpur(UP)INDIA

Abstract— **Our brain is our body's control center. It's part of the nervous system, which also includes the spinal cord and a large network of nerves and neurons. The nervous system including brain controls everything from your five senses to the muscles throughout your body.When your brain is damaged, it can affect many different things, including your memory, your sensation, and even your personality. Brain disorders include any conditions or disabilities that affect your brain. This includes those conditions that are caused by illness, genetics, or traumatic injury. Magnetic resonance imaging (MRI) is a medical imaging technique used in radiology to image the physiological processes of the body in both health and disease.MRI is a powerful tool used to see the internal structure of our body. In this approach, we are going to detect brain anomalies such as brain tumor, scizophrenia using MRI.We surveyed lots of paper to get optimal method used for detection of brain anomalies.We are going to analyse four basic steps for detection of brain anomalies.They are preprocessing , segmentation , feature extraction and classification and also we are going to suggest best method used for detection of brain anomalies.There are four sections in this paper.Section-I desribes introduction of our topic ,Section-II describes the literature survey of related papers, Section-III describes the descriptive analysis of the method used and Section-IV describes the conclusion.**

Keywords— **Magnetic Resonance Image, GLCM,SupportVector Machine,Median Filter,Medical Imaging**

I. INTRODUCTION

Brain serve as a centre of our nervous system. In modern neuroscience, the brain is treated as a biological computer, uses different mechanism as compared to electronic computer, but uses same sense to get the data and information from outside world, stores it and process it in the same way as Central Processing Unit (CPU) in computer. MRI is a powerful tool used to get image of internal structure of brain. MRI provides better quality images for the brain, the muscles, the heart and cancerous tissues compared with other medical imaging techniques such as computed tomography (CT) or X-rays.Medical imaging technique is a very useful in the area of image processing. Medical imaging are used to see the internal structure of the brain for diagnosis and detection of anomalies in the brain. Radiologist uses the MRI to detect the abnormalities in the brain and then take the surgical decision for removing these abnormalities. We are going to proposed an automated tools to diagnose these anomalies with the help of computer system. If these anomalies found early, they can be easily plan to removed. The proposed system consists of four steps. They are Preprocessing, Segmentation , Feature Extraction and Classification. The preprocessing is done using median filter techniques. Median filter is best among Mean Filter, Weiner Filter and Gaussian Filter . K-means clustering method is used for segmentation. GLCM (Gray Level Co-occurrence Matrix) and Gabor feature extraction techniques are used for feature extraction. Combining these two feature gives efficient and better result. Lastly Support Vector machine is used for Classification.

II. RELATED WORK

Kumari et al. used Magnetic Resonance Imaging tools in there framework. MRI is most valuable tools used in surgical and clinical surgery. Radiologist then examine the Magnetic Resonance Imaging to identify the presence of defective tissues. MRI may contain both normal and abnormal tissues. Further these separated abnormal tissues are inspected for brain tumor.There proposed method used the PCA for feature extraction from MRI data. These features are further classified using SVM. They used the dataset consists of 256 X 256 pixels, T2-weighted MRI brain images.They study the brain MRI of 60 pateints and found that 45 images were abnormal and remaining were normal.They found that there method were computationally effective and yielded good result.[1]

Sindhu et al. used the Brain MRI for detecting Brain Tumor. They used image processing techniques. There proposed methodology consists of four stages. They were image preprocessing , image segmentation ,feature extraction and classification.They improved the performance of detecting brain tumor in MRI by using image processing and neural network techniques. They surveyed more than 25 research papers for reviewing methods used particularly brain tumor in MRI.[2]

Paliwal et al. proposed method were used to identify the region of interest in the brain using Discrete Wavelet Transform based image decomposistion algorithm.They related the different brain activations to different brain functions and disorders by using MRI and EEG signals. They de-noising the image using wavelet transform and further feature extraction is used to classify the medical images.They proposed the different methods used for feature extraction in MRI scans.They improved the classification performance with the help of different classifiers, also compare the different classification techniques and get the best results.[3]

Kumari et al. proposed a method to extract the optimal features of brain tumor using MRI. There proposed system consists of three parts: preprocessing , segmentation and feature extraction. They used the best methods for all these parts. They used the median filtering for preprocessing for removing the noise , K-means clustering algorithms for segmentation and to recognize the tumor shape and size by using edge detection method.They found that median filter is best among mean filter ,weiner filter and gaussian filter for removing the noise in the image and further found that partitioned clustering like K-means is faster then heirarichal clustering and also found good result by using GLCM (Gray Level Co-occurrence Matrix) and Gabor feature extraction techniques for feature extraction.[4]

Lehana et al. worked on improving the quality of biomedical images using Aura Transform because these MRI are very useful to extract exact images . There were lots of mathematical methods are used. The objective is to extract maximum useful information from these images related proper functioning of the brain. In there proposed method, they used the aura based technique for enhancing the qulaity of MRI scans of the human brain.The relative distribution of pixel intensities with respect to a predefined structuring element is called Aura. The Aura matrix is formed by local distribution of pixel intensities of te given texture. By applying Aura transform, they get the significant results as compared to existing systems.[5]

Bandhopadhay et. al. proposed a system for segmentation of MRI scans by using a system of image registration and fusion theory . There system is relatively fast for diagnosis of the brain tumor as compared to existing systems. There proposed system consists of three parts. First part consists of registration of multiple MRI scans of the brain along with adjacent layers of brain. In second part, these images were further processed to get high quality image for segementation. Finally , K-means algorithm with dual localization methodology is used for segmented image. They showed some good result on given data and found significantly good segmented data as compared to existing data.[6]

Joseph et al. proposed a framework used to detect brain tumor in MRI scans. They first collected MRI scans, then they convert it into grey scales.Noise in the images were removes using median filter .Then this image was segmented using k-means clustering algorithm. Further they applied propose morphological filtering to that segmented image.They found good result by applying this framework.[7]

Although a number of recent studies have examined functional connectivity at rest, few have assessed differences between connectivity both during rest and across active task paradigms. Therefore, the question of whether cortical connectivity patterns remain stable or change with task engagement continues to be unaddressed.Cetin et al. collected multi-scan fMRI data on healthy controls (N=53) and schizophrenia patients (N=42) during rest and across paradigms arranged hierarchically by sensory load. They measured functional network connectivity among 45 non-artifactual distinct brain networks. Then, They applied a novel analysis to assess cross paradigm connectivity patterns applied to healthy controls and patients with schizophrenia. To detect these patterns, They fit a group by task full factorial ANOVA (Analysis of Variance) model to the group average functional network connectivity values. There approach identified both stable (static effects) and state-based differences (dynamic effects) in brain connectivity providing a better understanding of how individuals' reactions to simple sensory stimuli are conditioned by the context within which they are presented. There findings suggest that not all group differences observed during rest are detectable in other cognitive states. In addition, the stable differences of heightened connectivity between multiple brain areas with thalamus across tasks underscore the importance of the thalamus as a gateway to sensory input and provide new insight into schizophrenia.[8]

Allen et al. describe a simple data-driven approach to assess Functional Connectivity(FC) based on techniques like k-means clustering of windowed correlation matrix, sliding time-window correlation and spatial independent component analysis. They used GICA to split resting state data into functionally homogenous regions. They used the series of sliding windows to estimate the Time-varying FC . The resulting FC time series is used to determine brain regions with variable connections. They identify patterns of FC that reoccurs in time and across subject, using k-means clustering. They said these clusters as “FC states”. These FC states are very effective as compared to large-scale networks. These time varying FC is also used in the functional coordination between different neural systems.[9]

Segall et al. used the Gray Matter(GM) measures . GM consists of neuronal and glia cell bodies. They saw a reduction in GMD(Grey Matter Densities) as age increases. They used the GM to understand the both structural and functional connectivity. They investigate the spatial correspondence between structure and function. They applied spatial independent component analysis to both GMD maps and to resting state fMRI. These decomposed components were than compared by spatial correlation. They show correspondence between a single structural component and several resting-state functional components. They used the Multivariate approach, SBM(Source Based Morphometry), and found GM structural relationships several areas in brains where structure and function corresponds. They also concluded that age has a significant effect on structural components.[10]

Allen et al. established a baseline from which diagnostic should easily done. They also able to reduce unnecessary testing and able to optimizes sensitivity. They also identify the effect of age and gender on the resting-state networks(RSNs). They collected the data from the same scanner and preprocessed that data using automated analysis pipeline based in SPM (Statistical Parametric Mapping). These RSNs were evaluated in terms of three outcome measures: time course spectral power , spatial map intensity and functional network connectivity. They identify the substantial effect of age on all three measures. They also identify the smaller gender effect but found stronger intra-network connectivity in females and more inter-network connectivity in males. They provide the powerful and useful baseline for future investigations of brain networks in health and disease.[11]

Schizophrenia has often been conceived as a disorder of connectivity between components of large-scale brain networks.Lynall et al. tested this hypothesis by measuring aspects of both functional connectivity and functional network topology derived from resting state fMRI time series acquired from various peoples. They identify that people with schizophrenia, strength of functional connectivity was significantly decreased; whereas diversity of functional connections was increased. They correlated the Functional connectivity and topological metrics. They concluded that people with schizophrenia tend to have a less strongly integrated, more diverse profile of brain functional connectivity, associated with a less hub-dominated configuration of complex brain functional networks.[12]

Schizophrenia is hypothesized to involve disordered connectivity between brain regions. Currently, there are no direct measures of brain connectivity; functional and structural connectivity used separately provide only limited insight. Simultaneous measure of anatomical and functional connectivity and its interactions allow for better understanding of schizophrenia-related alternations in brain connectivity. Separate functional and anatomical connectivity maps were calculated and combined for each subject. Global, regional, and voxel measures and K-means network analysis were employed to identify group differences and correlation with clinical symptoms. Combining two measures of brain connectivity provides more comprehensive descriptions of altered brain connectivity underlying schizophrenia.[13]

III. Descriptive Analysis

Image Processing techniques are used to detect anamolies in brain using MRI.It is very challenging task for the recent researchers.This technique is useful in detecting automatically using computer system various brain anamolies such as Brain Tumor, Schizophrenia etc.This can be done in four steps.They are Image Preprocessing , Image Segmentation, Feature Extraction and Image Classification.Each of these steps are described are as follows:

1. Image Preprocessing: Preprocessing of the MRI scans is imortant step because there is lot of noise in MRI due to thermal effects.In this step RGB image of MRI scan is also converted into greyscale imageand also to reshape that MRI.Another advantage of this step to give an image which is easily segmented.Denoising is done using Median Filter Technique.This technique is very efficient as compare to other filtering techniques such as Weiner Filter,Gaussian filter etc.The brief description of Median Filter are as follows:

Median Filter: The median filter is a nonlinear digital filtering technique is used to remove noise.Removal of noise is a typical pre-processing step to improve the results of later processing.This techniques is used to remove the salt and pepper noise and poissons noise in the image and to enhance the image. Image is enhanced in the way that finer details are improved and noise is removed from the image. This technique is very useful in image processing because its working is similar to mean filter, it also preserves edge while removing noise but it is better then mean filter. In median filtering, the neighboring pixels are ranked according to brightness (intensity) and the median value becomes the new value for the central pixel. Median filters can do an excellent job of rejecting certain types of noise, in particular, “shot” or impulse noise in which some individual pixels have extreme values. In the median filtering operation, the pixel values in the neighborhood window are ranked according to intensity, and the middle value (the median) becomes the output value for the pixel under evaluation.The median filter is more expensive to compute than a smoothing filter. Clever algorithms can save time by making use of repeating values as the neighbourhood window is slid across the image. Median filters are nonlinear.

$$\mathbf{Median[S(x)+T(x)] \neq Median[S(x)] + Median[T(x)]}$$

This must be taken into account if you plan on summing filtered images.

2.Segmentation: The image segmentation is used to partition the MRI into region of interest or objects with respect to their features. Segmentation plays an important role in image processing to extract the suspicious region in the given MRI. The objective of the segmentation is to convert that MRI image into cluster so as to easily identify the region of interest or object. The segmentation method can be classified into three categories- Edge Based Methods, Region Based Methods and Pixel Based Methods. We are using K-means clustering method for segmentation, which is a pixel based method. Further, K-means clustering is suitable for medical image segmentation.

K-means Clustering Method: K-Means is a least-squares partitioning method that divide a collection of objects into K groups. The algorithm iterates over two steps:
1.Compute the mean of each cluster.
2.Compute the distance of each point from each cluster by computing its distance from the corresponding cluster mean. Assign each point to the cluster it is nearest to.
3.Iterate over the above two steps till the sum of squared within group errors cannot be lowered any more.

K-means Clustering Algorithm:
1.Set iteration = 1;
2.Choose randomly K-means m1,m2,m3 … mk

3.For each data point xi, compute distance to each of the means and assign the point the cluster with the nearest mean
4. iteration = iteration + 1
5Recompute the means based on the new assignments of points to clusters
6.Repeat 3-5 until the cluster centers do not change much

K-means clustering method is best among fuzzy C-means and C-means clustering algorithm, because Fuzzy C-means and C-means clustering are not used for relative object matching between two images.

3.Feature Extraction: Feature extraction is related to reduction of dimensions. When the input data to an algorithm is too large to be processed and it is suspected to be redundant, then it can be transformed into a reduced set of features. This process is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.Feature Extraction is the process of extracting some important feature from the given image.Feature extraction is helpful in detection of anamolies in brain and helps in surgical decisions.In this phase, we are using two feature extraction algorithms: they are GLCM (Gray Level Co-occurrence Matrix) and Gabor feature extraction techniques. Combination of these two techniques gives better results as compared to previous methods used for feature extraction. Both techniques are describe one by one:

Gray Level Co-occurrence Matrix (GLCM): The Gray-Level Co-occurrence Matrix (GLCM) is a well-known statistical technique for feature extraction. The GLCM is a calculation of how often different combinations of pixel gray levels could occur in an image The co-occurrence matrix and texture features were initially used for the automated classification of anamolies in MRI scans. The fourteen Haralick measures were used to extract useful texture information from the co-occurrence matrix[23].GLCM has now become the most commonly used tools for texture analysis because it can estimate image properties related to second-order statistics.First-order statistics can be obtained from mean and standard deviation and related to the properties of individual pixel.Second-order statistics can be obtained from GLCM by the co-occurrence of two pixels with respect to their positions. Co-occurrence matrices are calculated for the directions of 0 ° , 45 , 90 , and 135 . For each matrix, Angular Second Moment, Contrast, Correlation, Sum of Squares or Variance, Inverse Difference Moment, Sum Average, Sum Variance , Sum Entropy , Entropy , Difference Variance , Difference Entropy , Information Measure of Correlation and Cluster Tendency are obtained for the segmented MRI .

Gabor Technique: A Gabor atom (or function) was proposed by Hungarian-born electrical engineer Dennis Gabor in 1946[24]. Nowadays, Gabor functions are frequently used for feature extraction, especially in texture-based image analysis (classification, segmentation or edge detection) and in face recognition. Many of image processing tasks can be seen in terms of a wavelet transform. A set of Gabor filters with different frequencies and orientations may be helpful for extracting useful features from an image.In the discrete domain, two-dimensional Gabor filters are given by,

$$G_c[i,j] = Be^{-\frac{(i^2+j^2)}{2\sigma^2}} \cos(2\pi f(i\cos\theta + j\sin\theta))$$
$$G_s[i,j] = Ce^{-\frac{(i^2+j^2)}{2\sigma^2}} \sin(2\pi f(i\cos\theta + j\sin\theta))$$

where B and C are normalizing factors to be determined. 2-D Gabor filters have rich applications in image processing, especially in feature extraction for texture analysis and segmentation. f defines the frequency being looked for in the texture. By varying θ, we can look for texture oriented in a particular direction. By varying σ, we change the support of the basis or the size of the image region being analyzed.

4.Image Classification: The fourth and last step consists of classification of an extracted image. This step is very important due to detection of anamolies in the brain MRI.We are using Support Vector Machine for this step because SVM is the best method used for classification.Brief description of SVM are as follows:

Support Vector Machine: In machine learning, support vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis[25]. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

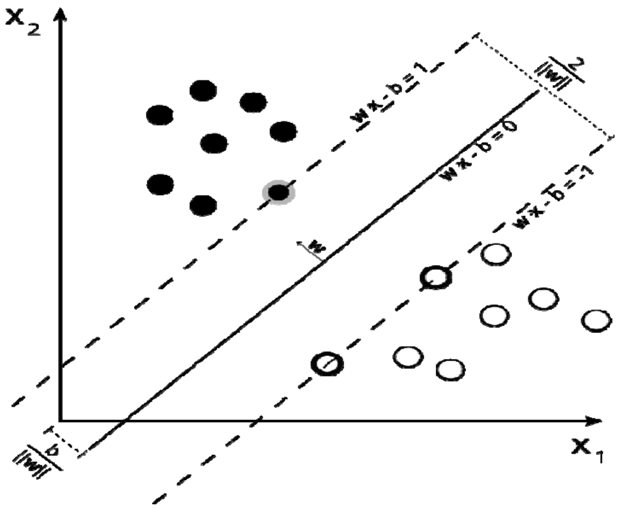
We are given a training dataset of n points of the form

$$(\vec{x}_1, y_1), \ldots, (\vec{x}_n, y_n)$$

where the y_i are either 1 or −1, each indicating the class to which the point $\vec{x}_i$ belongs. Each $\vec{x}_i$ is a p-dimensional real vector. We want to find the "maximum-margin hyperplane" that divides the group of points $\vec{x}_i$ for which $y_i - 1$ from the group of points for which $y_i = -1$, which is defined so that the distance between the hyperplane and the nearest point $\vec{x}_i$ from either group is maximized.

Any hyperplane can be written as the set of points $\vec{x}$ satisfying

$$\vec{w} \cdot \vec{x} - b = 0,$$



Maximum-margin hyperplane and margins for an SVM trained with samples from two classes. Samples on the margin are called the support vectors. where $\vec{w}$ is the (not necessarily normalized) normal vector to the hyperplane. The parameter $\frac{b}{\|\vec{w}\|}$ determines the offset of the hyperplane from the origin along the normal vector $\vec{w}$.

IV. CONCLUSION

We surveyed many research papers to get best solution to automatically detect anomalies in brain MRI using machine learning. We have studied many image processing techniques to get the requirements and properties in detection of Anomalies in brain. It was observed that our proposed methods are best and are relatively less computationally expensive, simple, and promising. These methods are best to predict brain abnormalities more effectively and more efficiently. We believe that, this article can give valuable understanding into this significant research topic and encourage new research. In the next phase of our work, we will plan to develop a new algorithm and compare their result with the existing algorithm for better results.

REFERENCES

[1] R. Kumari , R.K. Soni,"Classifying Brain Anomalies using PCA and SVM",International Journal of Scientific Research and Management (IJSRM) , Volume 2 , Issue 5, Pages 935-939, 2014

[2] A. Sindhu, S. Meera ,"A Survey on Detecting Brain Tumor in MRI Images using Image Processing Techniques", International Journal of Innovative Research in Computer and Communication Engineering, Volume 3, Issue 1, January 2015.

[3] S. Paliwal, Prof. S. Chouhan ,"Performance Analysis of Brain MRI using Muliiple Method",International Journal of Engineering Sciences and Research Technology, ISSN:2277-9655, January, 2015.

[4] S. Kumari, Sindhu M.,Sangeetha R."Feature Extraction of Brain Tumor using MRI", International Journal of Innovative Research in Science,Engineering and Technology,Volume 3 , Issue 3, March 2014.

[5] P. Lehana , S. Devi., S. Singh,"Investigations of MRI using Aura Transformations", Signal & image Processing : An International Journal(SIPIJ), Volume 3 , Issue 1, February 2012.

[6] S.K. Bandhopadhay, T.V.Paul ,"Automatic Segmentation of Brain Tumor from Multiple Image of Brain MRI ",International Journal of Application or Innovation in Engineering & Management (IJAIEM), Volume 2 , Issue 1,January 2013.

[7] R.P. Joseph, C.Singh , M.Manikandan,"Brain Tumor MRI Image Segmentation and Detection in Image Processing",International Journal of Research in Engineering and Technology, eISSN:2319-1163,pISSN:2321-73008.

[8] *M. Cetin, F. Christensen, C. Abbott, J. Stephen, A. Mayer, J. Canive, J. Bustillo, G. Pearlson,and V. D. Calhoun. Thalamus and posterior temporal lobe show greater inter-networkconnectivity at rest and across varying sensory loads in schizophrenia. NeuroImage, in press.*

[9] E. A. Allen, E. Damaraju, S. M. Plis, E. B. Erhardt, T. Eichele, and V. D. Calhoun. Tracking whole-brain connectivity dynamics in the resting state. Cerebral Cortex, pages 663–676, 2012.

[10] J. M. Segall, E. A. Allen, R. E. Jung, E. B. Erhardt, S. K. Arja, K. A. Kiehl, and V. D. Calhoun.Correspondence between structure and function in the human brain at rest. Frontiers inNeuroinformatics, 6(10), 2012.

[11] Allen E. A., Erhardt E. B., Damaraju E., Gruner W., Segall J. M., Silva R. F., Havlicek M., Rachakonda S., Fries J., Kalyanam R., Michael A. M., Caprihan A., Turner J. A., Eichele T., Adelsheim S., Bryan A. D., Bustillo J., Clark V. P., Feldstein Ewing S. W., Filbey F., Ford C. C., Hutchison K., Jung R. E., Kiehl K. A., Kodituwakku P., Komesu Y. M., Mayer A. R., Pearlson G. D., Phillips J. P., Sadek J. R., Stevens M., Teuscher U., Thoma R. J., Calhoun V. D. (2011). A baseline for the multivariate comparison of resting-state networks. Front. Syst. Neurosci. 5:2.10.3389/fnsys.2011.00002

[12] *Lynall M. E., Bassett D. S., Kerwin R., Mckenna P. J., Kitzbichler M., Muller U., Bullmore E. (2010). Functional connectivity and brain networks in schizophrenia. J. Neurosci. 30 9477–9487.*

[13] Skudlarski P., Jagannathan K., Anderson K., Stevens M. C., Calhoun V. D., Skudlarska B. A., Pearlson G. (2010). Brain connectivity is not only lower but different in schizophrenia: a combined anatomical and functional approach. Biol. Psychiatry 68 61–69

[14] C. E. Rasmussen and C. K. I. Williams. Gaussian Processes for Machine Learning. The MITPress, 2006.

[15] J. Vanhatalo, J. Riihim¨aki, J. Hartikainen, P. Jyl¨anki, V. Tolvanen, and A. Vehtari. GPstuff:Bayesian modeling with Gaussian processes. The Journal of Machine Learning Research, 14(1):1175–1179, 2013,3

[16] S. S¨arkk¨a, A. Solin, A. Nummenmaa, A. Vehtari, T. Auranen, S. Vanni, and F.-H. Lin. Dynamical retrospective filtering of physiological noise in BOLD fMRI: DRIFTER. NeuroImage, 60(2):1517–1527, 2012.

[17] S. S¨arkk¨a, A. Solin, and J. Hartikainen. Spatiotemporal learning via infinite-dimensionalBayesian filtering and smoothing. IEEE Signal Processing Magazine, 30(4):51–61, 2013.

[18] A. Solin and S. S¨arkk¨a. Infinite-dimensional Bayesian filtering for detection of quasiperiodicphenomena in spatiotemporal data. Physical Review E, 88:052909, 2013.

[19] I. Murray, R. P. Adams, and D. Mackay. Elliptical slice sampling. In International Conferenceon Artificial Intelligence and Statistics, pages 541–548, 2010.

[20] I. Murray and R. P. Adams. Slice sampling covariance hyperparameters of latent Gaussianmodels. In Advances in Neural Information Processing Systems, pages 1732–1740, 2010.

[21] J. Vanhatalo, J. Riihim¨aki, J. Hartikainen, P. Jyl¨anki, V. Tolvanen, and A. Vehtari. Bayesian modeling with Gaussian processes using the GPstuff toolbox. arXiv preprint arXiv:1206.5754,2012.

[22] A. Vehtari (corresponding author). GPstuff – Gaussian process models for Bayesian analysis.URL http://becs.aalto.fi/en/research/bayes/gpstuff/. Softwaretoolbox for Mathworks Matlab.4

[23] R. M. Haralick, K. Shanmugam and I. Dinstein "Textural features for Image Classification", IEEE Transactions on Systems, Man and Cybernetics, Vol.3, pp. 610-621, November 1973

[24] https://en.wikipedia.org/wiki/Gabor_filter

[25] https://en.wikipedia.org/wiki/Support_vector_machine#Linear_SVM