# Multiple sclerosis Lesion Detection via Machine Learning Algorithm based on converting 3D to 2D MRI images

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*Abstract*— **In the twenty first century, there have been various scientific discoveries which have helped in addressing some of the fundamental health issues. Specifically, the discovery of machines which are able to assess the internal conditions of individuals has been a significant boost in the medical field. This paper or case study is the continuation of a previous research which aimed to create artificial models using support vector machines (SVM) to classify MS and normal brain MRI images, analyze the effectiveness of these models and their potential to use them in Multiple Sclerosis (MS) diagnosis. In the previous study presented at the Cognitive InfoCommunication (CogInfoCom 2019) conference, we intend to show that 3D images can be converted into 2D and by considering machine learning techniques and SVM tools. The previous paper concluded that SVM is a potential method which can be involved during MS diagnosis, however, in order to confirm this statement more research and other potentially effective methods should be included in the research and need to be tested. First, this study continues the research of SVM used for classification and Cellular Learning Automata (CLA), then it expands the research to other method such as Artificial Neural Networks (ANN) and k-Nearest Neighbor (k-NN) and then compares the results of these.**

*Keywords*— *Support Vector Machines (SVM); Cellular Learning Automata (CLA); MS lesions Detection; 3D Images; MRI Images; Simulated Brain Database (SBD); SVM Tools; Machine Learning Techniques;*

## I. INTRODUCTION

CogInfoCom, the research field based on the synergy between info communications and the cognitive sciences, is driven by the continuously entangled landscape in which Information and Communications Technology (ICT) and humans interact and generate intermingled cognitive capabilities [1], [2]. CogInfoCom capitalizes on this intermingled environment and promotes existing synergies creating a more effective combination of engineering and theoretical applications. A primary output of these synergies improved in a way that does not provide just sensory communications but also the way information is stored in the brain. [3], [4], [5], [6].

This study is the continuation of a previous research which aimed to create artificial models using support Vector machines (SVM) to classify MS and normal brain MRI images, analyze the effectiveness of these models and their potential to use them in MS diagnosis. The previous study concluded that SVM is a potential method which can be involved during MS diagnosis, however in order to confirm this statement more research and other potentially effective methods should be included in the research and need to be tested [7], [8].

Multiple sclerosis (MS) a chronic autoimmune neurological disease of the Central Nervous System (CNS) which appears with great variability in its clinical manifestation [9]. MS adjust the morphology and the structure of the brain and can lead to disability in young adults (Loizou et al., 2011) [10], [11], [12]. However, with early recognition and treatment, quality of life can be highly improved and the relapse of MS lesions in the CNS can be experienced (Miller, 2019) [13], [14].

Magnetic Resonance Imaging (MRI) can detect the multifocal lesions in the CNS mainly associated with MS. In the previous research a simulated database of 2D images was used, which were generated from simulated 3D dataset, acquired from Brainweb database [15], [16]. This dataset contains 76 grayscale images classified into four classes, samples with normal brain images, mild MS samples, moderate MS samples and severe MS samples [17], [18], [19].

First, this study continues the research of SVM used for classification and then it expands the research to other method such as artificial neural networks (ANN) and k-nearest neighbor (k-NN) and then compares the results of these [20], [21], [22].

## II. DATASET

In the previous study the dataset used for model training and model testing was randomly generated, 70% (53 images) of the images used for training and 30% (23 images) for testing and the

process was repeated 10 times. In this case since the intention is to try more methods and compare them, the same dataset should be used for each test [23], [24], [25]. To achieve this the indices of the test dataset for each run are saved into a file. For each run, this file is read, processed and the samples which indices are contained in the file are used to test the methods, while the samples which indices are not contained in the file are used to train the models [26].

### III. RESULTS OF USING SVM

SVM is one of the most widely used machine learning method for binary pattern classification. SVM aims to construct a hyperplane set in an infinite dimensional space and find the hyperplane which represents the largest separation (margin) between the binary classes, so the goal is to find the maximum-margin hyperplane if it exists (Chao and Horng, 2015) [27], [28], [29], [30].

In the previous study two approaches were used since SVM is a binary classifier, however the current dataset can be divided into four mutually exclusive classes. In order to resolve this, in the previous study One-Against-One (1A1) and One-Against-All (1AA) techniques were introduced. The goal of 1AA technique to divide the N class dataset into N two-class cases, while 1A1 approach creates a model for each pair of classes so N(N-1)/2 models are built. In the previous study each method had an equal vote (Gidudu, Hulley & Marwala, 2007) [31], [32].

These approaches were reused for the new, fix dataset and to be able to compare the results of the methods the implementation was rerun to build models using the new trainsets and test-sets. For building the model MATLAB®

fitcsvm function was used with linear kernel function and with standardized predictor data (Table I.).

The average accuracy of the 1AA model is slightly worse compared to the previous model, however the 1A1 model produced a slightly better result. For the 2AllResult (the accuracy of the 1AA models), the previous average accuracy of the models was 0.77826087 while for 2OneResult (the accuracy of the 1A1 models) models was 0.765217391. so this run, 2OneResult has a slightly better average result and so far, it produced the best results in this run. Another interesting fact that in these runs no sample has been assigned to the 'more_results' flag, so in this case with equal votes for each method resulted in a deterministic result, however the number of no results in the case of 1AA method has a significant grow. In the previous study a rule for a voting system could be determined, which could have been tested in this study. This was not explained in the previous study, but the system would have been the following:

- 1AA method is used for the primary decision.
- if 1AA resulted in more results, the more severe result should be used.
- if 1AA resulted in no results, the 1A1 result should be used.
- if 1A1 has more results, the more severe should be used.

This rule should be rejected, because of the 1A1 has produced a slightly better result compared to the 1AA method and because no sample got more results in this case, so using such a technique wouldn't improve the overall results. For SVM, a different

TABLE I. SVM RESULTS USING LINEAR KERNEL FUNCTION

| ID | 2All Result | 2One Result | 2AllMore Result | 2OneMore Result | 2AllNo Result | 2OneNo Result | Differences | ST. DEV |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.739130435 | 0.652173913 | 0 | 0 | 6 | 0 | 0.391304 | 0.061488 |
| 2 | 0.739130435 | 0.782608696 | 0 | 0 | 6 | 0 | 0.26087 | 0.030744 |
| 3 | 0.695652174 | 0.739130435 | 0 | 0 | 7 | 0 | 0.304348 | 0.030744 |
| 4 | 0.826086957 | 0.826086957 | 0 | 0 | 4 | 0 | 0.173913 | 0 |
| 5 | 0.782608696 | 0.782608696 | 0 | 0 | 5 | 0 | 0.26087 | 0 |
| 6 | 0.739130435 | 0.782608696 | 0 | 0 | 6 | 0 | 0.26087 | 0.030744 |
| 7 | 0.739130435 | 0.739130435 | 0 | 0 | 6 | 0 | 0.26087 | 0 |
| 8 | 0.695652174 | 0.75 | 0 | 0 | 7 | 0 | 0.304348 | 0.03843 |
| 9 | 0.782608696 | 0.826086957 | 0 | 0 | 5 | 0 | 0.217391 | 0.030744 |
| 10 | 0.695652174 | 0.782608696 | 0 | 0 | 7 | 0 | 0.304348 | 0.061488 |
| AVG | 0.743478261 | 0.766304348 | 0 | 0 | 5.9 | 0 | 0.273913 | 0.01614 |

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TABLE II. SVM RESULTS USING RBF KERNEL FUNCTION

| ID | 2All Result | 2One Result | 2AllMore Result | 2OneMore Result | 2AllNo Result | 2OneNo Result | Differences | ST. DEV |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.739130435 | 0.782608696 | 0 | 0 | 6 | 0 | 0.260869565 | 0.030744 |
| 2 | 0.739130435 | 0.782608696 | 0 | 0 | 6 | 0 | 0.260869565 | 0.030744 |
| 3 | 0.695652174 | 0.739130435 | 0 | 0 | 7 | 0 | 0.304347826 | 0.030744 |
| 4 | 0.826086957 | 0.826086957 | 0 | 0 | 4 | 0 | 0.173913043 | 0 |
| 5 | 0.782608696 | 0.826086957 | 0 | 0 | 5 | 0 | 0.217391304 | 0.030744 |
| 6 | 0.739130435 | 0.739130435 | 0 | 0 | 6 | 0 | 0.260869565 | 0 |
| 7 | 0.739130435 | 0.739130435 | 0 | 0 | 6 | 0 | 0.260869565 | 0 |
| 8 | 0.695652174 | 0.782608696 | 0 | 0 | 7 | 0 | 0.304347826 | 0.061488 |
| 9 | 0.782608696 | 0.826086957 | 0 | 0 | 5 | 0 | 0.217391304 | 0.030744 |
| 10 | 0.695652174 | 0.739130435 | 0 | 0 | 7 | 0 | 0.304347826 | 0.030744 |
| AVG | 0.743478261 | 0.778260870 | 0 | 0 | 5.9 | 0 | 0.256521739 | 0.024595 |

kernel function can be tested to examine the method efficiency [33]. This kernel function is the radial basis function (rbf) and the result can be seen in (Table II).

For the 1AA method the rbf kernel function produced exactly the same results compared to the linear kernel function, however in the case of 1A1 the results are slightly better for these tests. These runs also did not produce more results for any of the elements of the datasets.

## IV. RESULTS USING NEURAL NETWORKS

A neural network (NN) is built from simple, connected processors called neurons which form a sequence of real-valued activations. Special type of neurons, called input neurons are activated through the environment, other neurons are activated through the connected previously activated, weighted neurons. The learning process of a neural network is finding the optimal weights to be able to perform the desired results (Table III). The construction of a network depends on the problem and how the neurons are connected (Schmidhuber, 2015) [34].

MATLAB® provides easy to use, flexible tools to create, test and analyze neural networks. In this study a simple artificial neural network (for the exact parameters see Appendix A), with 15 layers and 10 max epochs were trained using the sample train- and test datasets which were used to build the SVM models.

The average accuracy of the NN network is significantly worse compared to the SVM models, however the 9th NN test produced an especially low accuracy. Here the model supposedly did not conver-gate, so the whole test was repeated using 50 max epochs.

This modification significantly improved the results of the NN and for test 2 and test 9 the model reached 100%

TABLE III. ACCURACY OF NN USING 10 AND 50 MAXIMUM EPOCHS

| ID | Accuracy (10 epochs) | Accuracy (50 epochs) |
|---|---|---|
| 1 | 0.82608696 | 0.95652174 |
| 2 | 0.82608696 | 1 |
| 3 | 0.60869565 | 0.82608696 |
| 4 | 0.69565217 | 0.86956522 |
| 5 | 0.7826087 | 0.95652174 |
| 6 | 0.60869565 | 0.7826087 |
| 7 | 0.86956522 | 0.86956522 |
| 8 | 0.69565217 | 0.82608696 |
| 9 | 0.26086957 | 1 |
| 10 | 0.82608696 | 0.95652174 |
| AVG | 0.7 | 0.90434783 |

accuracy. However, this could imply that the models are over-trained, which means that they produce the desired results for this sample, however for different samples they would not perform this well. Cross validation technique is used to avoid this situation, however more independent tests with additional samples would be needed to confirm or reject the case of overtraining [35], [36], [37].

So far NN reached the best average accuracy and supposedly the NN result would be improved if the number of epochs would be increased. In case of neural networks, the challenge is to determine the structure of the network, for instance should it be feed forward or recurrent and other important structural decisions also highly effect the desired behavior of the networks, for instance the number of layers, the type of this layers, the number of neurons in each layer etc.
For k-NN MATLAB® provides a complex framework to train the models and use the models for prediction [38].

The models are created using the "fitcknn" function which provides a highly parameterizable, flexible solution for model training. In the study, several parameters are used, the number of neighbors and the distance metrics were called "Minkowski" distance and Euclidean distance were used.

Minkowski distance was tested with $k = 3..7$ values. Compared to the SVM and the NN, the average accuracy produced by k-NN is the worst. The best result was reached with $k = 4$, however a tendency can be observed, with increasing k the average accuracy was decreased [28], [39], [40], [41].

## V. RESULTS USING K-NN

It is reasonable to expect those samples which are close using an appropriate metric can be classified into the same class and it is also applicable to assume, that one unclassified observation can be classified to the class where its closest neighbors are classified (Dudani, 1976) [21]. The simplest k-nearest neighbor (k-NN) computes the distance (or similarity) between the sample and the values in the training set (Table IV)., restricts the maximum number of neighbors to k training samples and assign the class to the sample which the majority of the k neighbors belong (Grudzinski, 2008) [42], [43], [44].

The k-NN test was repeated with $k = 1..7$ and using Euclidean distance as the distance metrics. The results can be seen in (Table V).

Using the Euclidean distance for building the model did not improve the average accuracy for $k = 3..7$, however the average accuracy for $k = 1$ is significantly better compared to other k values. This can be due to the variety which can be experienced in MS lesions in the dataset, however more analysis would be needed to prove that.

TABLE IV.    K-NN RESULTS USING MINKOWSKI DISTANCE WITH $k = 3..7$

| ID | Accuracy3 | Accuracy4 | Accuracy5 | Accuracy6 | Accuracy7 |
|----|-----------|-----------|-----------|-----------|-----------|
| 1 | 0.695652 | 0.695652 | 0.695652 | 0.652174 | 0.652174 |
| 2 | 0.565217 | 0.565217 | 0.565217 | 0.521739 | 0.565217 |
| 3 | 0.478261 | 0.478261 | 0.478261 | 0.521739 | 0.434783 |
| 4 | 0.695652 | 0.869565 | 0.73913 | 0.695652 | 0.478261 |
| 5 | 0.695652 | 0.521739 | 0.521739 | 0.478261 | 0.521739 |
| 6 | 0.565217 | 0.565217 | 0.521739 | 0.478261 | 0.478261 |
| 7 | 0.521739 | 0.521739 | 0.521739 | 0.478261 | 0.478261 |
| 8 | 0.608696 | 0.652174 | 0.565217 | 0.565217 | 0.565217 |
| 9 | 0.608696 | 0.608696 | 0.565217 | 0.521739 | 0.26087 |
| 10 | 0.434783 | 0.478261 | 0.434783 | 0.478261 | 0.521739 |
| AVG | 0.586957 | 0.595652 | 0.56087 | 0.53913 | 0.495652 |

TABLE V.    K-NN RESULTS USING EUCLIDEAN DISTANCE WITH k=1..7

| ID | Accuracy1 | Accuracy2 | Accuracy3 | Accuracy4 | Accuracy5 | Accuracy6 | Accuracy7 |
|----|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| 1 | 0.826087 | 0.695652 | 0.695652 | 0.695652 | 0.695652 | 0.652174 | 0.652174 |
| 2 | 0.782609 | 0.652174 | 0.565217 | 0.565217 | 0.565217 | 0.521739 | 0.565217 |
| 3 | 0.782609 | 0.565217 | 0.478261 | 0.478261 | 0.478261 | 0.521739 | 0.434783 |
| 4 | 0.913043 | 0.782609 | 0.695652 | 0.869565 | 0.73913 | 0.695652 | 0.478261 |
| 5 | 0.826087 | 0.695652 | 0.695652 | 0.521739 | 0.521739 | 0.478261 | 0.521739 |
| 6 | 0.826087 | 0.565217 | 0.565217 | 0.565217 | 0.521739 | 0.478261 | 0.478261 |
| 7 | 0.782609 | 0.521739 | 0.521739 | 0.521739 | 0.521739 | 0.478261 | 0.478261 |
| 8 | 0.913043 | 0.695652 | 0.608696 | 0.652174 | 0.565217 | 0.565217 | 0.565217 |
| 9 | 0.826087 | 0.608696 | 0.608696 | 0.608696 | 0.565217 | 0.521739 | 0.26087 |
| 10 | 0.73913 | 0.478261 | 0.434783 | 0.478261 | 0.434783 | 0.478261 | 0.521739 |
| AVG | 0.821739 | 0.626087 | 0.586957 | 0.595652 | 0.56087 | 0.53913 | 0.495652 |

## VI. COMPARING THE RESULTS

The best average accuracy was produced by NN however that is not the only tool to compare results. In this case, the ratio of fake positive and fake negative values also can be counted. In this case the dataset contains four classes, however it can be simplified by assuming that normal is negative and MS effected samples are positive. Therefore, fake positive is, when the classifier assigned a positive class to the sample, however it is actually negative and fake negative is a sample which the classifier assigned a negative value, but it is actually positive. Using this assignment differences between the severity of MS do not counted, just the difference between normal and MS samples and the goal is to minimize these values. The below table (Table VI.) contains the average number of fake positive and fake negative values for every method tested in this study.

NN using 50 maximum epochs managed to minimize the average number of fake positive results and k-NN using Euclidean distance metrics with $k = 1$ and all SVM models also reached good average results. In case of fake negative, 1AA SVM models managed to minimize the average values with zero fake negative results in the samples 1A1 SVM and NN with epoch 50.

TABLE VI.    AVERAGE NUMBER OF FAKE POSITIVE AND FAKE NEGATIVE RESULT BY METHOD

| Method | Fake positive | Fake negative |
|---|---|---|
| 1AA SVM linear | 1.5 | 0 |
| 1A1 SVM linear | 1.5 | 0.8 |
| 1AA SVM rbf | 1.5 | 0 |
| 1A1 SVM rbf | 1.5 | 0.9 |
| NN epoch 10 | 2.2 | 3 |
| NN epoch 50 | 1 | 1 |
| k-NN Euclidean k=1 | 1.1 | 0.7 |
| k-NN Euclidean k=2 | 3 | 1 |
| k-NN Euclidean k=3 | 3.1 | 0.9 |
| k-NN Euclidean k=4 | 3.1 | 1.2 |
| k-NN Euclidean k=5 | 2.9 | 1.7 |
| k-NN Euclidean k=6 | 3.2 | 1.3 |
| k-NN Euclidean k=7 | 3.3 | 1.5 |
| k-NN Minkowski k=3 | 3.1 | 0.9 |
| k-NN Minkowski k=4 | 3.1 | 1.2 |
| k-NN Minkowski k=5 | 2.9 | 1.7 |
| k-NN Minkowski k=6 | 3.2 | 1.3 |
| k-NN Minkowski k=7 | 3.3 | 1.5 |

## VII. CONCLUSION

SVM is a useful tool for MS disease diagnosis process. In order to be able to make more appropriate and satisfactory assumptions, more tests are required. Brainweb dataset is a useful source of data to generate images with different parameters, which can change the parameters such as brightness, contrast and etc. of the images. Tests with SVM, NN and k-NN proved that with the current results NN is the method which should be widely investigated, however SVM also should not be dropped because of it can minimize the number of fake negative values. For further investigation a new dataset could be built using different simulation parameters. Even artificial neural networks for the 3D simulations can be built if the proper hardware resources are available, but naturally the best dataset would be the data of real MS patients. The current idea is to focus on neural networks, however SVM should be used to confirm the results of NN.

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## X. APPENDIX A

```
layers = [
    imageInputLayer([217 181 1])

convolution2dLayer(3,8,'Padding','same')
    batchNormalizationLayer
    reluLayer
    maxPooling2dLayer(2,'Stride',2)

convolution2dLayer(3,16,'Padding','same')
    batchNormalizationLayer
    reluLayer
    maxPooling2dLayer(2,'Stride',2)

convolution2dLayer(3,32,'Padding','same')
    batchNormalizationLayer
    reluLayer
    fullyConnectedLayer(4)
    softmaxLayer
    classificationLayer];

 options = trainingOptions('sgdm', ...
    'InitialLearnRate',0.01. ...
    'MaxEpochs',50. ...
    'Shuffle','every-epoch', ...
    'Verbose',false);
```