The Wechsler Adult Intelligence Scale-Revised is a test designed and applied comprehensively for classifying the cognitive skills of adults. Different intellectual profiles on a sample population of 414 individuals, have been obtained to measure the relationship between the mental functioning or psychopathological disorder of the individuals based on the data through the Wechsler Adult Intelligence Scale-Revised test. The relevant data have been collected and considered as input neuron for Artificial Neural Networks and Support Vector Machine Radial Basis Function kernel Algorithms. Classification accuracy, time elapsed for training procedure and accuracy rate have been obtained through Multi Layer Perceptron. The training data is split as follows: 70% is the training data, 15% is the validation data and 15% is the test data. In addition, in Support Vector Machine, time elapsed and accuracy rate have been evaluated based on 5-fold cross validation method. As a result, we will show the importance of Working Memory profile (Numbering, Assembly Ability) of The Wechsler Adult Intelligence Scale-Revised test on adults for the analysis of psychopathological disorder.

Keywords:The Wechsler Adult Intelligence Scale-Revised, Clinical Classification, Artificial Neural Networks Algorithm, Support Vector Machine Algorithm
1 Introduction

The Wechsler Adult Intelligence Scale-Revised (WAIS-R) globally measures and demonstrates adults’ capacity with respect to their voluntary movements, logical reasoning and coping with relevant factors at ease [9] [11] [14] [24] [29]. WAIS-R is a test that measures intelligence which is regarded as a superior mental ability. The test is multidimensional and has multi determination feature. The test is comprised of six verbal subtests and five performance subtests. Besides these subtests, the test is used for the calculation of verbal IQ and functional IQ at universal terms [2] [5] [9, 10, 11] [14] [16] [21] [29]. References cited [2] [4, 5] [10] [12, 13] [16] [18, 19] [21] [23] [30] present valuable information on the details and content concerning WAIS-R test [32].

WAIS-R is a test designed and applied for the research of adults cognitive skills comprehensively. Different intellectual profiles have been used to measure the correlation between General knowledge & Verbal fluency, Verbal conceptual, Attention & Concentration, Spatial visual motor coordination. These skills have been considered in order to measure the relationship between the mental functioning of the patients and psychopathological data in the WAIS-R test [32]. In certain recent papers, these tests have also been taken into consideration for manifesting the existence of a mental disorder [32].

Recent literature reveals that there have already been some attempts to relate the importance of WAIS-R test with the mental disorder. Yadav [26] and his team presented a new neuron model, with multiplicative neuron that performs multiplication operation rather than simple summation. Their simulation results show that the proposed neuron model, used in a feed forward neural network, performs better than existing multilayer networks (MLN). Cui [31] and his team studied how the artificial neural networks (ANN) can be used to interpret student performance on cognitive diagnostic assessments (CDAs) and evaluate the performances of ANN using simulation results. The current investigation focuses on the third component as researchers examine the use of ANN as a powerful nonparametric statistical method for diagnostic classification. Akande [17] and his team did a study on the importance of concrete compressive strength prediction in structure and building design. In their paper, they studied the performance of support vector machine (SVM). The conventional method of determining the strength of concrete is complicated and time consuming hence artificial neural network (ANN) is widely proposed in lie of this method. However, ANN is an unstable predictor due to the presence of local minima in its optimization objective. It was found that SVM displayed a slightly better performance compared to ANN and is highly stable. Kalogirou [27] illustrated how artificial neural networks (ANN) and genetic algorithms (GAs) played an important role in modelling and prediction of the performance of various energy systems in buildings. Results presented prove
the potential of artificial neural networks and genetic algorithms as design tools in many areas of energy applications in buildings. Gupta [1] focused on developing empirical models for predicting surface roughness, tool wear and power required in turning operations. These response parameters were mainly dependent upon cutting velocity, feed and cutting time. Three competing data mining techniques, response surface methodology (RSM), artificial neural networks (ANN) and support vector regression (SVR), were applied in developing the empirical models. It was found that ANN and SVR models were much better than regression and RSM models for predicting the three response parameters. Moraes [25] and his team studied document-level sentiment classification to automate the task of classifying a textual review, as expressing a positive or negative sentiment. On the benchmark data set of Movies reviews, artificial neural network (ANN) outperformed support vector machine (SVM) by a statistically significant difference, even on the context of unbalanced data. Their results also confirmed some potential limitations of both models like the computational cost of SVM at the running time and ANN at the training time. Ren [15] showed the essential role of classification of micro calcification clusters from mammograms in computer-aided diagnosis for early detection of breast cancer, where (SVM) and (ANN) were two commonly used techniques. A new strategy namely balanced learning with optimized decision making was proposed to enable effective learning from imbalanced samples, which was further employed to evaluate the performance of ANN and SVM in this context. When the proposed learning strategy was applied to individual classifiers, the results on the DDSM database demonstrated that the performance from both ANN and SVM was considerably enhanced. Even though ANN outperformed SVM when balanced learning was absent, the performance from the two classifiers became very similar when both balanced learning and optimized decision making were employed. Quintana [22] and his team studied mild cognitive impairment (MCI), a transitional state between normal aging and Alzheimer disease (AD). The aims of this study were to develop, train, and explore and develop the ability of ANN to differentiate MCI and AD, and to study the relevant variables in MCI and AD diagnosis. Their results indicated that ANN had an excellent capacity to discriminate MCI and AD patients from healthy controls. These findings provided evidence that ANN could be a useful tool for the analysis of neuropsychological profiles regarding clinical syndromes. Karaca [32] applied WAIS-R data set on Artificial Neural Networks with 13 healthy individuals and 401 patients. The algorithms in the study were Feed Forward Back Propagation and Cascade Forward Back Propagation. The aim of the team’s experimental studies was to measure the diagnostic classification success using these algorithms. The best performance in classification belonged to Feed Forward Back Propagation algorithm.

Classification of the disorder among algorithms was compared with clas-
sification performances. While doing the classification with Artificial Neural Networks Multi Layer Perceptron (ANN - MLP) algorithm and Support Vector Machine Radial Basis Function (SVM - RBF) kernel, two different data sets were used. The first data set consists of data obtained from profiles like Verbal Comprehension, Perceptual Reasoning, Working Memory and Processing Speed. The second data set is comprised of data which has been obtained after having removed the Working Memory profile (Numbering, Assembly Ability) from the first set of data. The study underlines the necessity of accuracy while applying the Working Memory of WAIS-R test on the patients. This study includes data of WAIS-R test administered on both females and males. It is aimed to contribute to literature since it intends to identify the classification of individuals as healthy and unhealthy through machine medium.

2 Material and Methods

The materials under investigation are the data sets taken through a WAIS-R test on a population of 414 healthy and unhealthy individuals. The analytical methods applied on these data sets are derived from ANN - MLP and SVM - RBF kernel algorithms.

2.1 Data sets

For this study, the test has been applied on 414 individuals, constituting both females (4 of them are healthy, 196 of them are unhealthy individuals) and males (9 of them are healthy, 205 of them are unhealthy individuals) aged between 14-87. The relevant data for the study has been collected over a period of ten years from the Unit of Psychiatry of Department of Clinique Neuroscience, Surgery of Psycho diagnostic of the Federico II University of Naples. The tool used to evaluate the intellectual profile of patients is WAIS-R scale (Wechsler Adult Intelligence Scale Revised). WAIS-R has been used on grounds of reliability and frequency of use as tools across the world. Furthermore, it ensures the estimation of various mental processes as to the cognitive functioning of adults. As for the education levels of the individuals, it can be stated that there are different groups that can be defined as follows: 3rd grade, 5th grade (Elementary School), 8th grade (Middle School), 12th grade (High school) and University degree [32].

This study has parameters that include problems regarding the mental functioning and psychopathology (affective, mental and behavioral scopes) of the patients. For Data Set 1, 21 parameters are the following: School Education, Gender, Age, Similarity, Logical Deduction, Vocabulary, Information, Memory, Comparison, Verbal Information Volume (VIV), Quantity Information Verbal (QIV), Finiteness or Closure, Ordering Ability, 3 Dimensional
Modeling, Quantity Information Performance (QIP), Arithmetic, Assembly Ability, Quantity Information Total (QIT), Performance Information Verbal (VIP), Performance Information Verbal (VIT), Full Scale Intelligence Quotient (DM). Data Set 2 includes the application of 19 parameters are School Education, Gender, Age, Similarity, Logical Deduction, Vocabulary, Information, Memory, Comparison, VIV, QIV, Finiteness or Closure, Ordering Ability, 3 Dimensional Modeling, VIP, QIP, QIT, VIT, DM. There are two classes, Healthy/Unhealthy, on the output layer of the application. The reason for carrying out the evaluation with two different data sets was the necessity of applying the profiles taken from WAIS-R test thoroughly. The reason for carrying out the evaluation with two different data sets was the necessity of applying the profiles taken from WAIS-R test thoroughly. If such profiles are not applied thoroughly, the diagnosis of the disorder cannot be accurate. This is of great significance both for physicians while diagnosing the disorder and for those who perform classification in machine learning algorithm.

2.2 Methodology

General structure of the ANN - MLP and SVM - RBF kernel algorithms belonging to the study and the significant data in the diagnosis of disorder applied on the input layer of these methods are explained.

2.2.1 Artificial Neural Network

The structure of a basic artificial neuron is a lot simpler than that of a biological neuron. There are mainly data obtained from the external environment or other neurons, namely inputs, weights, addition function, activation function and outputs in an artificial neuron. Data received from outside is bound to the neuron by means of the weights. The weights determine the impact of the relevant input. The total function is calculated by the net input. The net input is a product of the relevant weights. The activation function calculates the net output during the operation which also yields the neuron output [3] [6] [20] [31].

\[
O = f(W.X + b)
\]

\[
W = w_1, w_2, w_3, ..., w_n
\]

\[
X = x_1, x_2, x_3, ..., x_n
\]  

As it can be seen from Equation 1, Equation 2, Equation 3 Output (O) is the product of the X inputs and the weights (W) applied onto the X inputs.

\[
net = \sum_{i=1}^{n} w_i x_i + b
\]  

As it can be seen from Equation 1, Equation 2, Equation 3 Output (O) is the product of the X inputs and the weights (W) applied onto the X inputs.
\[ O = f(\text{net}) \] (3)

The denotation above can be used \[32\].

### 2.2.2 Multi Layer Perceptron

Multi layer perceptron (MLP) is a feed-forward ANN system where more than one layer is used between the input and output layers. In these medium layers, named as hidden layer, there are procedural elements whose knots are not directly bound to the input and output layers. The value on the input does not change until the weights reach the appropriate point. The outputs are calculated with the desired responses, and if required error is stated. Error denotation is used for changing the weights from the hidden procedure elements to the output unit. Instead, the impact of each unit on the output unit errors should be known. This is done by taking the sum of the error denotations of the output units bound to hidden unit for each errored unit \[6\] \[20\] \[28\]. Based on the equations 2,3,4,5; x input \(x_0 = +1\) is added into the input layer and hence expanded.

\[
W = \text{sigmoid}(w_h^T x) = \frac{1}{1 + \exp\left(-\sum_{j=1}^{d} w_{hj} x_j + w_{h0}\right)}, h = 1, \ldots, H \tag{4}
\]

\(y_i\) outputs make up the second learning layer which gets the input neurons in the hidden layer.

\[
y_i = v_i^T z = \sum_{h=1}^{H} v_{ih} z_h + v_{i0} \tag{5}
\]

There always exists an additional value unit shown as \(z_0\) in the hidden layer, its value is always \(+1\) and it shows the weights \(v_{i0}\) going towards the outputs.

### 2.3 Support Vector Machine

Support Vector Machine (SVM) is a modern classifier. SVM is capable of doing good generalizations structuring linear classification boundaries in multidimensional space by means kernel \[7\] \[8\] \[28\]. SVM design is split by hyperplane \[7\] that signifies the decision boundaries named “support vectors”. The class prediction is performed based on these decision boundaries.

In SVM, a maximum level of accuracy is attained in the estimation of class prediction concerning a new data set which is formed through the use of optimum decision boundary from the training data. Afterwards, its accuracy
rate has been analyzed by obtaining class accuracy [7]. The following can be indicated for SVM with two classes:

\[ w^T x^t + w_0 \geq +1 if r^t = +1 \]  
(6)

\[ w^T x^t + w_0 \leq -1 if r^t = -1 \]  
(7)

The application is conducted with a vector which is able to be split linearly as 1 or -1 with class representation based on the Equations 6 and 7 [8]. The hyperplanes of the samples are not found merely adjacent to the line. For a better generalization they are supposed to endure within a certain distance. The distance of the nearest samples on both sides of the boundary is the margin; and this margin should be as high as possible for an optimum generalization [8].

3 Results and Discussion

A record of 414 individuals, both healthy and unhealthy subjects, is included in our study. Data received according to WAIS-R has been applied as input for the ANN - MLP and SVM - RBF kernel algorithms. There are two output neurons on the output layer representing the unhealthy and the healthy individuals.

Machine learning tool was MATLAB [33] used for the ANN - MLP and SVM - RBF kernel model. During our experimental studies, the same parameters were used for Data Set 1 and Data Set 2 in MLP algorithm. Sigmoid function as the transfer function on the hidden layer and linear transfer function for the output layer were made through a network structure that is a 10 layered advanced version network. The hidden layer neuron number for Data Set 1 and Data Set 2 in MLP architecture has been selected as 10. MLP learning parameters are as follows: validation set proportion has been selected as 0.20, and learning rate as 0.15. The training procedure is maximum 100 iterations, error threshold value is 0.01, and momentum is set as 1.00e-08. Based on Figure 1 a) according to Data Set 1 in WAIS-R, as a result of the training procedure that lasted 42 seconds for 10 iterations, the performance value has been obtained as 0.00118. For the validation procedure set as Epoch 8 the best validation result has been obtained at Epoch 2. Based on Figure 1 b) according to Data Set 2 in WAIS-R, as a result of the training procedure that lasted 2 minutes and 17 seconds for 46 iterations, the performance value has been obtained as 1.94e-09. The best validation result has been yielded at Epoch 46.

It has been observed that when Numbering and Assembly Ability parameters are removed from the data set, training procedure takes a longer time.
While the time elapsed is 42 seconds for Data Set 1, it is 2 minutes and 17 seconds for Data Set 2. When Mean Squared Error is analyzed, the following can be stated: through the removing of Numbering and Assembly ability parameters from Data Set 2, it has been seen that a better result in classification accuracy has been obtained compared to Data Set 1 for all the three procedures, namely training, validation and test.

Based on Figure 2 a) related to Data Set 1 5-fold cross validation procedure, as a result of training procedure of SVM RBF kernel algorithm lasted 5 seconds, it yielded an accuracy performance for classification amounting to 96.9%, error rate was obtained as 3.1%. 400 of 414 instances have been classified accurately. Based on Figure 2 b) related to Data Set 2 5-fold cross validation procedure, as a result of training procedure of SVM RBF kernel algorithm lasted 7 seconds, it yielded an accuracy performance for classification amounting to 96.1%, error rate was obtained as 3.9% of 414 instances have been classified accurately.
Conclusion, the accuracy rate performance in classification obtained by using SVM algorithm RBF kernel proved to be better in Data Set 1 compared to that in Data Set 2. In the class representation for WAIS-R data set belonging to individuals through ANN and SVM, the relationship between the Numbering and Assembly Ability parameters are presented in Figure 3.

![Figure 3: Thin-plate spline interpolant graph through the class representation of WAIS-R Numbering and Assembly Ability attributes.](image)

Although a better classification performance has been obtained in Data Set 2 in MLP, the time elapsed for the training procedure is 1 minute and 31 seconds longer than that of Data Set 1. For the SVM RBF kernel training procedure, there has been found out to be a 0.8% better classification performance in Data Set 1 compared to Data Set 2.

4 Conclusions

Administered on 414 individuals for the identification of the patients problems regarding their mental functioning, issues related to affect, cognition and behavior WAIS-R test has provided data for this study. Data received from the individuals has been applied on MLP and SVM (RBF kernel) which are among the machine learning methods. Based on the test, the classification of the individuals as healthy and unhealthy has been performed. Two different data sets have been taken as reference while obtaining the classification performance. Data Set 1 includes all the parameters obtained from WAIS-R test. Data Set 2 is comprised of units after having the Numbering and Assembly Ability parameters removed from Data Set 1. These two Data Sets have been applied on ANN - MLP and SVM - RBF kernel Algorithms. The study has presented the significance of applying WAIS-R parameters in a through way for the diagnosis of the individuals disorders. Hence, it can be said that this study can be cited as a reliable system which physicians can benefit from in the field of medicine. This study provides contribution to literature since it stresses the importance of disorder identification in machine medium regarding the WAIS-R parameters. The contribution can be related to the comparison of accuracy rate derived from the disorder classification and the required time...
for the training procedures with respect to ANN-MLP and SVM-RBF kernel algorithms. Besides, as the number of data in our database increases, this rate could prove be a good reference not only for the algorithms in this study but also for other methods available in the scope of engineering.

**Acknowledgements.** Dr. Yeliz Karaca would like to thank Prof. Diana Galletta, her team at the Unit of Psychiatry of Department of Clinique Neuroscience, Surgery of Psychodiagnostic of the Federico II University of Naples for their input in the study for sharing their data on mental functions. The authors would also like to express their appreciation to the patients in the study.

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**Received: October 30, 2016; Published: December 3, 2016**