Predicting Dementia Risk Factors Based on Feature Selection and Neural Networks

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Abstract: Dementia is a disorder with high societal impact and severe consequences for its patients who suffer from a progressive cognitive decline that leads to increased morbidity, mortality, and disabilities. Since there is a consensus that dementia is a multifactorial disorder, which portrays changes in the brain of the affected individual as early as 15 years before its onset, prediction models that aim at its early detection and risk identification should consider these characteristics. This study aims at presenting a novel method for ten years prediction of dementia using on multifactorial data, which comprised 75 variables. There are two automated diagnostic systems developed that use genetic algorithms for feature selection, while artificial neural network and deep neural network are used for dementia classification. The proposed model based on genetic algorithm and deep neural network had achieved the best accuracy of 93.36%, sensitivity of 93.15%, specificity of 91.59%, MCC of 0.4788, and performed superior to other 11 machine learning techniques which were presented in the past for dementia prediction. The identified best predictors were: age, past smoking habit, history of infarct, depression, hip fracture, single leg standing test with right leg, score in the physical component summary and history of TIA/RIND. The identification of risk factors is imperative in the dementia research as an effort to prevent or delay its onset.

Keywords: Dementia prediction; feature selection; genetic algorithm; neural networks

1 Introduction

Dementia refers to a wide range of neurological diseases which are responsible for progressive cognitive deterioration, memory loss, and an accumulation of disabilities, leading to increased morbidity and mortality [1]. In advanced stages, patients can suffer from a cognitive decline, so severe as to interfere with their social functioning, professional lives, leisure activities, and can lead to a complete loss of independence [2]. Dementia patients portray a poor quality of life, which is related to severe symptoms like confusion, disorientation, mood swings, impaired gait and speech, behavioral changes, acute memory loss, and difficulty in swallowing etc. [2,3].

Dementia is characterized by a vast societal impact, and its consequences range beyond the patients. The families, which often are the main caregivers of the dementia patients, are at risk of negative health outcomes themselves, such as accentuated strain, stress and depressive symptoms, as a consequence of the emotional and financial burden of care [4,5]. The impact of dementia on healthcare systems around the world is also substantial, representing a significant cost with prospects to increase. It is estimated that, in 2015, the direct and indirect costs of dementia corresponded to 1.1% of the worldwide total domestic product reaching US$ 818 billion, a number that is expected to grow to US$ 2 trillion by 2030 [6].

Dementia is more common in older adults and many individuals think that it is an inescapable byproduct of aging which might be wrong. Dementia is not a natural aspect of aging; rather, it ought to be recognized as a significant cognitive impairment that disrupts your normal existence. Actually, a variety of ailments and injuries to the human brain are the fundamental causes of dementia development. To aggravate this scenario, there is an insufficient understanding of dementia's mechanisms and etiology. Further, the available symptomatic treatments do not show a substantial improvement in regards to the cognition deterioration [7]. This makes the health economics of dementia different from other chronic conditions that affect the older population. While conditions like diabetes have most of their costs of care directed to disease-modifying interventions, in the case of dementia, roughly 83% of the costs of care are directed to social and informal care aimed at compensating for the cognitive decline of the patients and its consequences [2].

An extensive body of research has been addressing the topic of dementia for decades. However, the focus of the research, especially in regards to prognosis, is focused on identifying and validating biomarkers for pharmaceutical research, which is very important to make advancements in finding a potential treatment. However, this research mainly focuses on patients at a prodromal stage (mild cognitive impairment) and their evolution, or not, to dementia, as shown in a systematic literature review of dementia prognosis [8]. Thus, people who are already vulnerable to dementia. Another important action area that should be considered in order to reduce the impact of dementia is prevention. Indeed, risk reduction is one of the focal points of the World Health Organization's worldwide strategy for dementia public health response [6]. The identification of risk factors is imperative to support healthcare efforts for the prevention of diseases. However, evidence suggests that the brains of people who get dementia might begin to undergo changes as soon as 15 years before their diagnosis [9,10]. Hence, precautionary measures and plans might benefit from taking the time span into consideration.

Given this scenario, this study aims at proposing a method for ten-year prediction of dementia using multifactorial data consisting of demographic, socioeconomic, and lifestyle factors, medical history, biochemical testing, physical examination, psychiatric evaluation, and other health tools, using a genetic algorithm (GA) for the selection of features. After feature selection, two types of classification techniques are used: artificial neural networks and deep neural networks. In this study, we suggest

two kinds of hybrid diagnostic systems. i.e., GA_ANN and GA_DNN for the prediction of dementia and its risk factors. The proposed diagnostic systems help to find the finest set of features from the above-mentioned multifactorial data to predict dementia in 10 years. Through the identification of such features, it could be possible to delay or avoid dementia in elderly individuals. The proposed diagnostic system also helps in the early prediction of dementia.

It is imperative to remember that there are various dementia subtypes i.e., Vascular dementia, Alzheimer's disease, Frontotemporal dementia and dementia with Lewy Body are the most common. Mixed pathologies, on the other hand, are fairly rare, especially when Alzheimer's disease coexists with Vascular or Lewy Bodies dementia. Furthermore, unusual variants of Alzheimer's disease are infrequently misdiagnosed. The study mentioned here does not distinguish between subtypes, and the word "dementia" refers to all kinds of dementia.

2 Dataset Description

The dataset for this study was obtained from the Swedish National Study on Aging and Care (SNAC). The SNAC is a continuous consortium which is accumulating multifactorial data from the Swedish elderly with the purpose of developing reliable, robust, persistent datasets that will constitute a platform that allows for aging research and care for older adults [11]. The SNAC was built as a project with several functions to study social and health care for elderly, and it contains a database comprised of documents pertaining to physical examination, psychological evaluation, social variables, lifestyle variables, health records, and so on. To extend this study, in the future we will obtain datasets from different cohorts of SNAC and develop different ML techniques for dementia prediction.

Blekinge, Nordanstig, Kungsholmen, and Skne are the four places where the SNAC data is taken. They represent two Swedish counties, borough and municipality, respectively: Blekinge, Nordanstig, Kungsholmen, and Skne. This study used the SNAC-Blekinge baseline data, which was gathered between 2000 and 2003. Despite the evidence from the literature that external conditions might take part in dementia development [12,13]. This research uses generic criteria and makes no distinctions between urban and rural environments. The following criteria are used to eliminate subjects from this study: (i) individual who had dementia at the beginning; (ii) individuals with missing data on the outcome variable; (iii) individual with at least 10 percent missing data in the input variables; (iv) participants who died before end of the 10-year trial; and (v) individuals who were confirmed to have dementia before the 10 years trial, because they may already have significant cognitive decline. The SNAC Blekinge baseline contained 1402 people. Following the implementation of the specified screening, the study sample was comprised of 726 participants (313 male, 413 female subjects), from which 91 (12.5 percent) had dementia at the 10-year period and 635 (87.5 percent) did not. Table 1 displays the statistics of the study population in the collected data.

Table 1: Statistics of dementia dataset

Age-group	Male	Female	Sum	Dementia-patients
60	82	82	164	02
66	75	95	170	06
72	50	74	124	10
78	41	50	91	17

(Continued)

Table 1: Continued

Age-group	Male	Female	Sum	Dementia-patients
81	35	46	81	19
84	26	42	68	22
87	04	19	23	14
90+	00	05	05	01
Total	313	413	726	91

The variables from the SNAC-Blekinge database were considered according to data from the dementia disorder literature [14,15]. It is worth noting that this study did not take into account dementia subtypes because mixed pathologies are widespread and unusual subtypes are commonly mistaken as Alzheimer's disease [3]. Furthermore, all variables utilized in the SNAC venture were selected based on proof of relevance in ageing (wellness, social and support structure, lifestyle determinants, material circumstances, personal resources), as well as facts on community care consumption [1]. From the baseline of the SNAC study (2000–2003), 75 variables were determined from the main groups: demographics, societal, lifestyle, health history, blood sample, physical assessment, physiological, and the evaluation of several health tools linked to dementia evaluation. Table 2 presents a list of the variables that have been selected.

Table 2: Summary of selected variables

Variable_category	Variables_names	Total
Demographic	Sex, Age	02
Social	Social Network, Schooling, Religion, Loneliness, Devout Activities, Support Network, Voluntary Work	07
Lifestyle	Social Activities, Weak Exercise, Alcohol, Present Smoker, Physical-Workload, Past Smoker, Leisure Activities, Cigarettes per Day, Physically Hard Activities, Alcohol Quantity, Work Status	11
Medical history	No. of Medications, Arrhythmia, Stroke, TIA/RIND, Developmental Disabilities, Diabetes Type1, Epilepsy, Myocardial Infarction, Cancer, Cardiovascular Ischemia, Other Psychiatric Diseases, High Blood Pressure, Snoring, Atrial Fibrillation, Heart Failure, Sleep Apnea, Family History of Importance, Hip Fracture, Depression, Head Trauma, Diabetes Type 2, Thyroid Disease, Parkinson's Disease	22
Biochemical test	Protein Analysis, Hemoglobin Analysis	02
Physical examination	BMI, Heart Rate, Pain in the previous 4 weeks, BP on the Right Arm, Dental Prosthesis, Number of Teeth, Right Arm Hand Strength in a 10s Interval, Hand Strength in Left, Single Leg Standing, Heart Rate Lying, Feeling of Safety standing from Chair, Single-Leg Standing (Right), Rising from a Chair	13

(Continued)

Table 2: Continued

Variable_category	Variables_names	Total
Psychological	Memory Decline, Sense of Identity Memory Decline 2, Memory Loss, Personality Change, Abstract Thinking	06
Health instruments	Comprehensive Psychopathological Rating Scale, Backwards Digit Span Test, Mini-Mental State Examination, Sense of Coherence, Livingston Index, Instrumental Activities of Daily Living, Mental Composite Score, EQ5D Test, Digit Span Test, Physical Composite Score, Activities of Daily Living, Clock Drawing Test	12

The target variable in this study is the diagnosis of dementia in the ten-year period of the SNAC. This diagnosis is determined by doctors using the recommendations from the 10th iteration of the International Classification of Diseases and Related Health Problems (ICD-10) and the Diagnostic and Statistical Manual of Mental Disorders (DSM-5).

3 Data Preparation

In this investigation, the KNN imputation was applied separately to values from the majority and minority classes. Because the samples are utilized to construct the prognostic estimates and the data shows a considerable class imbalance (12.5 percent in the minority class against 87.5 percent in the majority class), the danger of compromising with the minority class in dataset was decreased. This is congruent with evidence of missing data from binary solution decision trees, that has proven independent imputation enhances classification accuracy [16].

We conducted normalization and standardization procedures on the selected data after addressing missing items in the dataset to enhance the quality of the dataset [17]. After data normalization, the efficiency of ML models improves. Therefore, because the dementia dataset contains only numeric values with varying scales, we used a standard-scaler function on it. The standard-scalar function rescales the data value range, resulting in a mean of 0 and a standard deviation of 1 [18]. ML models do well when the number of samples in the dataset is nearly equally balanced. Unfortunately, dementia is a rare event, so balancing sampling is required in order to construct datasets.

4 Proposed Model

The proposed diagnostic system is made up of two components that are merged to form a single Blackbox model. The fundamental rationale for integrating the two elements into a single block is because they complement each other. The first part is a feature selection module of the proposed ML model, while the second is a prediction model. Datamining methodologies are used for feature selection to increase the performance of ML models [19,20]. A GA is used in the feature selection module to pick the optimal subset of features which are applied to the DNN, which acts as a predictive model. Fig. 1 shows the working of the presented method.

GA is a powerful search technique because of its inherent parallelism and capacity to explore complex space using natural selection and population genetics. Using a GA to select input features in a neural network is easy. Every prospective feature is assigned to an individual (Boolean chromosome), where a bit "1" indicates that the related feature is chosen and a bit "0" indicates that the feature

is rejected. A breeding process that favors fitter individuals produces successive populations. An individual's fitness is seen as a measure of the success of the input vector. Individuals with better fitness will be more likely to contribute to the children of the next generation.
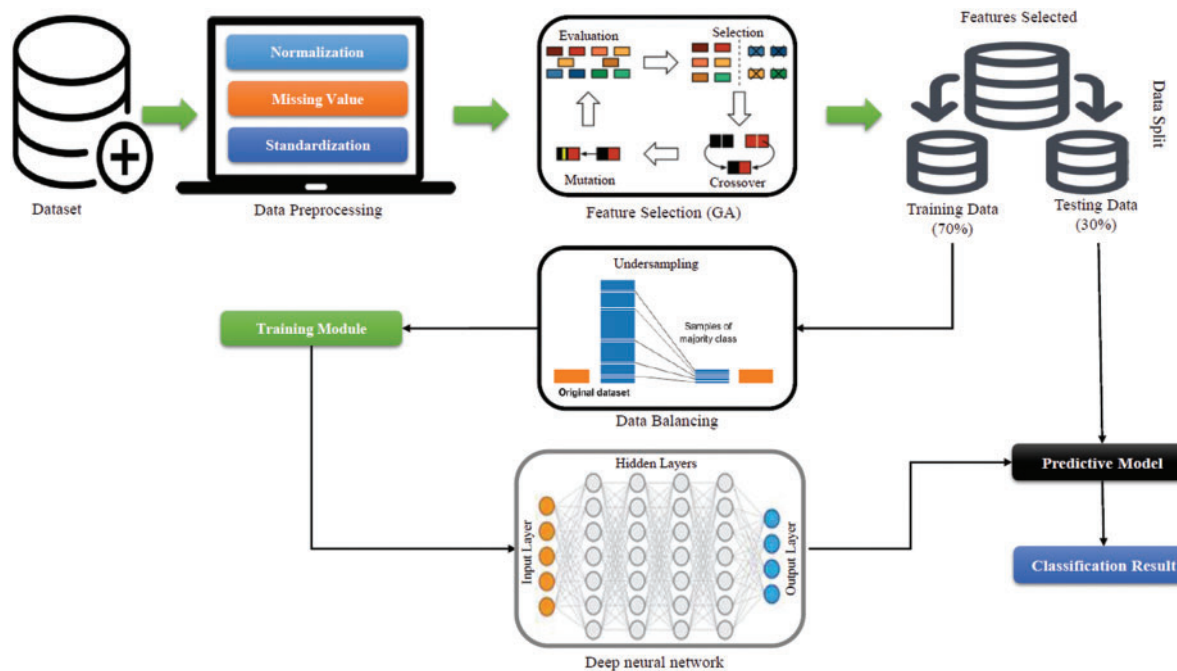

Figure 1: Block diagram of the newly proposed diagnostic system

Three key actions can collaborate to produce the future generation. In replication, individual strings are reproduced directly into the next generation. The greater a person's fitness value, the more likely that individual will be duplicated. Existing individuals are mated to create new ones. The chance of a string being chosen as a parent is fitness-based. At random, a number of crossing points are chosen at random. Copying from one parent until a crossing point can be reached, then replicating from the other parent and continuing the process as required, results in the formation of a child. Crossover points in a M bit string can range from 1 to M-1. Strings generated through reproduction or crossover can then be modified. This includes switching the state of bits at random. Mutation is required for future generations to merely reorganize genetic material.

Following the selection of features from a GA, data partitioning occurred for the purposes of training and testing of the newly developed prediction model. Unfortunately, the data consists of imbalanced classes, which might lead to bias in the results. ML models trained on imbalanced data tend to be biased by favoring the majority class while disregarding the minority class [20,21]. Because minority class instances are trained rarely during the training phase, minority class prediction is uncommon, overlooked, and unreported [22].

Each individual is assessed after the birth of a new generation, and the procedure is repeated until a sufficient subset of features is determined. The following are the steps of a GA algorithm for feature selection:

Algorithm 1: GA for feature selection

Initialization
(1) *Ns*: Population size
(2) *Ip*: Initial population along *Ns* subsets of *S*
(3) *Cp*: Crossover probability
(4) *Mp*: Mutation probability
(5) *Mg*: Maximum no. of generations
(6) *T*: 0
(7) **Start**
(8)   Fitness evaluation of *Ip*
(9)   **While** (*T < Mg* and *Ns* does not converge) do
                   Breeder Selection
                   Crossover along *Cp*
                   Mutation along *Mp*
                   Fitness evaluation of *Ip* replication
                   Dispersal
                   T + 1
(16) **End**

Various strategies have been proposed in the literature for dealing with imbalanced data [23]. The resampling approach is the most widely utilized method. This approach consists of two methods: undersampling and oversampling. Oversampling duplicates minority class samples to equalize the size of each class in training data. Some majority class samples are deleted throughout the training phase to balance the size of each class. As a result, when training a model using balanced data, it is expected to exhibit impartial behavior. Various undersampling approaches have been proposed in the literature. However, it has been observed that random undersampling is the most straightforward way and performs likewise to other methods [24]. As a result, in this work, we employ the random undersampling technique to optimize the training process and eliminate bias in the models developed. The random undersampling strategy randomly picks participants from the larger class in each iteration/fold of a cross-validation trial until the training data is balanced. As a result, the training process is optimized or balanced. It is critical to note that the resampling approaches are only applied to the training data during each cross-validation cycle and not to the complete data prior to cross validation. Fig. 2a provides the original distribution of the dataset where it can be seen that healthy subject samples number 635 in comparison to patients' samples of 91. The training data is only undersampled and the sample of healthy subjects and patient are equal of 81 that can be depicted in Fig. 2b.

After the balancing procedure, the data is trained on a DNN. Even if the DNN is used with an ideal subset of features, poor performance will arise from an ineffective DNN design. The fundamental explanation for such poor performance is that underfitting occurs when the DNN architecture chosen for classification has inadequate capacity [24,25]. In this situation, the DNN will perform poorly on both training and testing data. Nevertheless, if indeed the DNN structure has too much ability, it will lead to biased estimates towards the training data, resulting in better training data quality but worse testing data performance. As a result, we need to find the optimum DNN structure that can work effectively on testing and training data. To grasp the relationship between DNN structure and DNN capabilities, we must first appreciate DNN formulation. The neural network is built as follows:
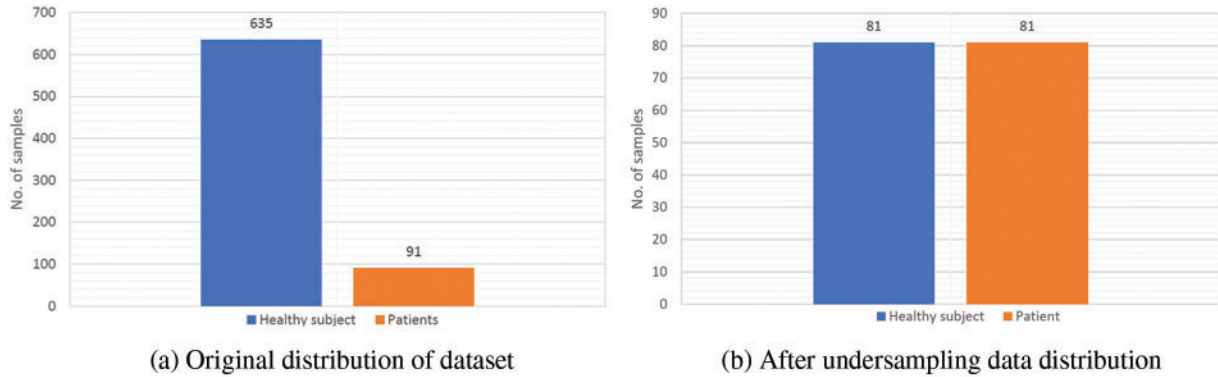
(a) Original distribution of dataset   (b) After undersampling data distribution

Figure 2: Overview of data distribution before and after undersampling

The computer system builds neural networks based on mathematical representations of the cerebral cortex. The perceptron or node is the central component of the neural network model [26]. Nodes are organized into groupings known as layers. Artificial neurons work in the same way as real neurons do. When an artificial neuron receives one or more inputs from nearby neurons, it analyzes the information and transfers the results to the next perceptron. Weights are a form of connection that is used to link artificial neurons. During the output computation, the input data χ_i is either positive or negative weighted. For the solution of a problem under examination, an intrinsic criterion δ value and weights are applied. The outcome is determined on each node by multiplying the input values χ_n by the associated weight ϖ_n, which is adjusted by the predefined intrinsic criterion δ. The output is then computed using an activation function (β), as shown in the Eq. (1).

$$\varepsilon_i = \beta \left(\sum \varpi_n . \chi_n - \delta \right) \tag{1}$$

Linear or nonlinear transfer can occur. The hyperbolic is used for nonlinear function tangents. The sigmoid function $\beta(\varepsilon_i)$ is performed as an output value at the next layer Eq. (2). The form of the sigmoid function is linked to λ. The increase in parameter λ value enhanced the sigmoid function's nonlinearity:

$$\beta(\varepsilon_i) = \frac{1}{[1 + exp(-\lambda\varepsilon_i)]} \tag{2}$$

The neural network is constructed by connecting the artificial neurons. We call a neural network model ANN, if it has only a single hidden layer [27]. Whereas, if a neural network structure has more than one hidden layer, it is referred to as a DNN [27].

Initially, we set the maximum number of features which can be selected from the dataset is 15. This means GA generates 15 subsets of features from the dataset and each subset of features contain maximum number of features up to 15 or minimum number of features is 1. Each time the subset of features which are selected by the GA are tested against accuracy using DNN, the efficacy of the subset features is saved. This process repeated until we find the optimal subset of features along with the best accuracy. The grid search technique is used to optimize the DNN architecture. The architecture of DNN has 8 hidden layers with 15 neurons in each hidden layer. The working of the proposed diagnostic system based on GA_DNN can be depicted from the given below algorithm:

Algorithm 2: Proposed diagnostic system (GA_DNN)

Input: {N_F: Feature size, β: Hyperparameters}
Output: {O_F: Best subset of features, β_o: optimal}
(1) **Initialize**
(2)   Best_Acc = 0
(3)   Max_Fea = 15
(4)   **For** 1 = Max_ Fea
(5)   **For** 1 = β_{max}
(6) O_F = generated by GA
(7)   Acc = O_F & β
(8)   **If** (Acc> Best_Acc)
                                Best_Acc = Acc
                                Store O_F and β as a β_o
                         End If
                    End For
               End For
(14) Display O_F, β_o & Best_Acc

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5 Validation and Evaluation

Previously, the performance of expert diagnostic systems was tested using holdout validation approaches. The dataset must be split into two halves: one for the purpose of training and one for testing. Previously, the researchers divided the data into different train-test split ratios. In their studies, Das et al. in [28] and Paul et al. in [29] employed holdout validation procedures for dividing the dataset into 70%–30% ratios, for model training and performance assessment, respectively. As a result, we used the identical data partitioning criteria for train-test purposes. To assess the efficacy of ML models, many measures such as sensitivity, accuracy, specificity, confusion metric, Matthew's correlation coefficient (MCC), area under the curve (AUC), f-score and the ROC are available. We chose accuracy, sensitivity, specificity, MCC, and F1-score as assessment metrics for the newly suggested models GA_ANN and GA_DNN, where accuracy is given as the percentage of perfectly categorized subjects, specificity is the ultimate categorization of healthy people, and sensitivity is the correct categorization of dementia.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

where TP stands for the number of true positives, FP stands for the number of false positives, TN stands for the number of true negatives, and FN stands for the number of false negatives.

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)\,(TP + FN)\,(TN + FP)\,(TN + FN)}} \tag{6}$$

MCC for ML and statistics is used to measure the binary classification models. The MCC value ranges between 0 and 1. A value of 1 indicates absolute contradiction between prediction and observation, a value of 1 indicates accurate prediction, and a value of 0 indicates random prediction. In

addition, another assessment metric, the receiver operating characteristic (ROC) curve, was used in this investigation. The ROC is an established tool for quantitatively assessing the quality of a prediction model. We have deployed cross validation using k-fold (k = 5) to validate the performance of the developed model.

6 Experimental Results

In this section, two different types of diagnostic systems are developed. Furthermore, tests are carried out to evaluate the efficacy of the suggested diagnostic systems. In the initial experiment, GA-ANN is constructed and stimulated, whereas GA_DNN is used in the second experiment. The GA algorithm is employed to generate a subset of features and the subset of features is applied to ANN for the classification of dementia in the first experiment. In the following experiment, GA is used to build a subset of features, while DNN is employed for classification. We have also analyzed the performance of other state-of-the-art ML algorithms for dementia prediction in the third experiment. Python programming software was used in all of the experiments.

6.1 Experiment 01: Feature Selection by GA and Classification by ANN

In this experiment, GA is employed in the first step and ANN is utilized as a classifier in the second step. The feature selection component employs a GA to exclude noisy and irrelevant information from the dataset, whilst the ANN is used as a predictive model. Using only a subset of features, the suggested diagnostic method achieves 90.36% accuracy. The optimum feature subset is achieved for $N_F = 07$, where N_F denotes the size of the feature subset and F_S denotes the selected features which are 0, 03, 06, 40, 41, 54, 65. Table 3 summarizes the simulation findings.

Table 3: Results of several feature subsets for dementia prediction based on GA_ANN where N_F: number of features, F_S: feature selected by GA, Acc.$_{Train}$: Accuracy on training data, Acc.$_{Test}$: Accuracy on testing data, Sens.: Sensitivity, Spec.: Specificity, MCC: Matthew's correlation coefficient

N_F	F_S	Acc.$_{Train}$	Acc.$_{Test}$	Sens.	Spec.	MCC
02	19, 52	63.24	65.13	58.42	45.38	0.3268
03	07, 32, 52	55.15	61.92	48.78	55.23	0.2955
04	06, 40, 44, 52	46.32	25.22	38.45	66.75	0.2018
05	03, 23, 54, 58, 75	34.56	33.94	25.17	18.80	0.1239
06	01, 03, 50, 51, 61, 71	36.76	37.15	46.55	42.24	0.1875
07	0, 03, 06, 40, 41, 54, 65	85.95	90.36	92.81	89.79	0.4586
08	0, 22, 24, 28, 40, 44, 52, 68	50.26	61.00	65.48	70.19	0.3041
09	03, 24, 28, 39, 40, 54, 59, 61, 75,	45.59	50.91	65.81	50.55	0.3533
10	0, 03, 12, 31, 40, 44, 56, 57, 73, 75	58.82	71.10	81.00	70.65	0.4152
12	03, 11, 21, 24, 30, 31, 40, 51, 58, 68, 70, 75	85.95	87.61	90.86	88.79	0.4327
75	0-75 (All features)	78.64	82.00	88.65	90.56	0.4238

The last row of the Table 3 shows a scenario where all of the features are used for the prediction of dementia using ANN. It can be seen that the best accuracy of 82.00% is obtained after tweaking the design of ANN using a grid search technique and all features. Thus, it is obvious that the provided model is competent since it provides greater performance with the fewest features. Furthermore, the

feature selection module improves the performance of optimized ANN's by 8.00%. Table 3 displays the outcomes of various subsets of features based on different evaluation metrics i.e., accuracy, sensitivity, specificity and MCC. Moreover, we have also evaluated the performance of the proposed GA_ANN model based on ROC, where proposed GA_ANN model obtained an AUC of 90% based on k-fold (k:5) evaluation metric in comparison to conventional ANN using all features from the dataset, as seen in Fig. 3.
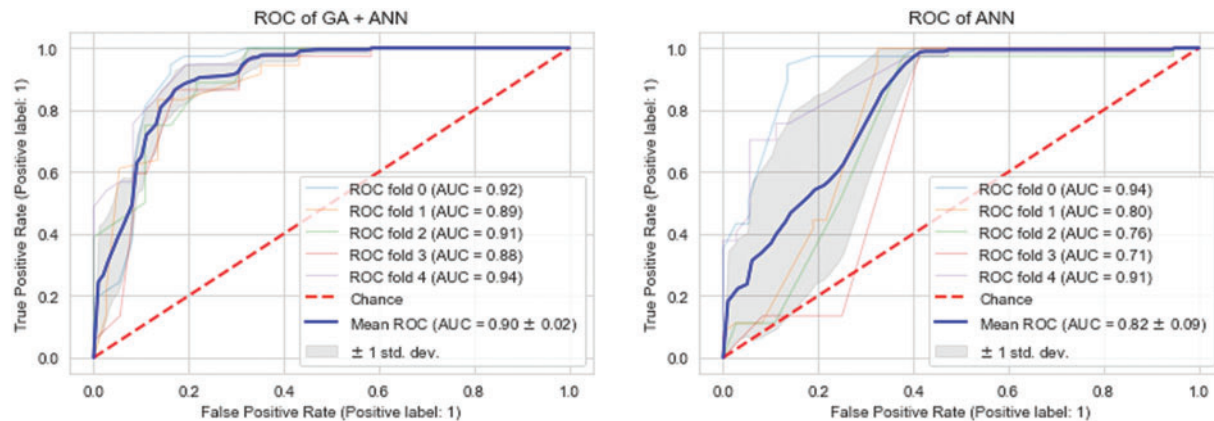

Figure 3: ROC comparison of proposed model (GA_ANN) with traditional ANN model

6.2 Experiment 02: Feature Selection by GA and Classification by DNN

In this experiment, GA is employed in the first stage, whereas DNN is deployed in the second. The feature selection module employs GA to exclude noisy and irrelevant information, whilst the second model is used as a predictive model. Using only a subset of features, the suggested diagnostic method achieves an accuracy of 93.15%. For $N_F = 3$, the size of the feature subset is determined by GA. The subset of selected features is 06, 44, 52 on which the highest accuracy was achieved by DNN. The proposed also obtained an accuracy of 93.15% with an improved training accuracy of 90.36% while using 09 features from the dataset. The subset of features which are selected by the proposed model GA_DNN are 03, 17, 23, 27, 36, 40, 55, 57, 75. The results of the experiment are shown in Table 4 The experiment was conducted using all features of the dataset and DNN for the classification to validate the efficacy of the proposed GA_DNN. The grid search approach was used to optimize the DNN architecture. A ten-layer neural network obtained the highest accuracy of 87.00%. The size of the first layer is equal to the number of features determined by GA. The hidden layer of the neural network contains 10 layers with 16 neurons each, and the output layer has just one neuron. The final row in Table 2 represents a case in which the DNN uses all features to forecast dementia. As a result, it is evident that the feature selection module (GA) improves DNN performance by 6.00%. Furthermore, GA_DNN outperforms GA_ANN in terms of performance. Table 4 displays the outcomes of various subsets of features based on different evaluation metrics, i.e., accuracy, sensitivity, specificity and MCC.

The ROCs are used to evaluate the effectiveness of the proposed model. The best model is the one with most area under the curve (AUC) in the ROC chart. The ROC that points in the upper left corner is deemed to be the best. Fig. 4 shows that the proposed GA_DNN model presented the highest area under the curve, 93.00%, in comparison to the DNN area under the curve of 87.00% while using all the features in the dataset. Thus, the proposed model is more efficient and accurate while using lesser

number of features from the dataset. Furthermore, the proposed GA_DNN is also more efficient than GA_ANN by comparing the ROC curve of both models.

Table 4: Results of several feature subsets for the dementia disease dataset based on GA_DNN where NF: number of features, FS: feature selected by GA, Acc._Train: Accuracy on training data, Acc._Test: Accuracy on testing data, Sens.: Sensitivity, Spec.: Specificity, MCC: Matthew's correlation coefficient

| N_F	F_S	Acc._Train	Acc._Test	Sens.	Spec.	MCC
2	01, 52	50.42	68.49	70.45	65.40	0.3541
3	06, 44, 52	88.00	93.15	91.32	95.87	0.4657
4	03, 22, 24, 75	86.12	82.87	89.75	78.45	0.4282
5	05, 20, 40, 51, 52	71.55	69.00	75.49	68.32	0.3758
6	04, 17, 40, 44, 45, 52	78.00	84.24	89.26	79.56	0.4346
7	03, 06, 21, 23, 24, 71, 75	72.85	65.39	55.41	70.23	0.3333
9	03, 17, 23, 27, 36, 40, 55, 57, 75	90.36	93.15	95.75	91.59	0.4788
7	03, 12, 31, 40, 64, 73, 75	86.11	93.00	86.16	90.77	0.4700
11	0, 03, 17, 22, 37, 40, 51, 52, 58, 71, 73	90.23	92.85	95.76	90.00	0.4686
12	02, 03, 04, 13, 19, 26, 29, 32, 40, 63, 71, 75	82.85	75.68	74.35	81.92	0.4515
75	0–75 (All features)	91.00	87.00	92.73	85.96	0.4562
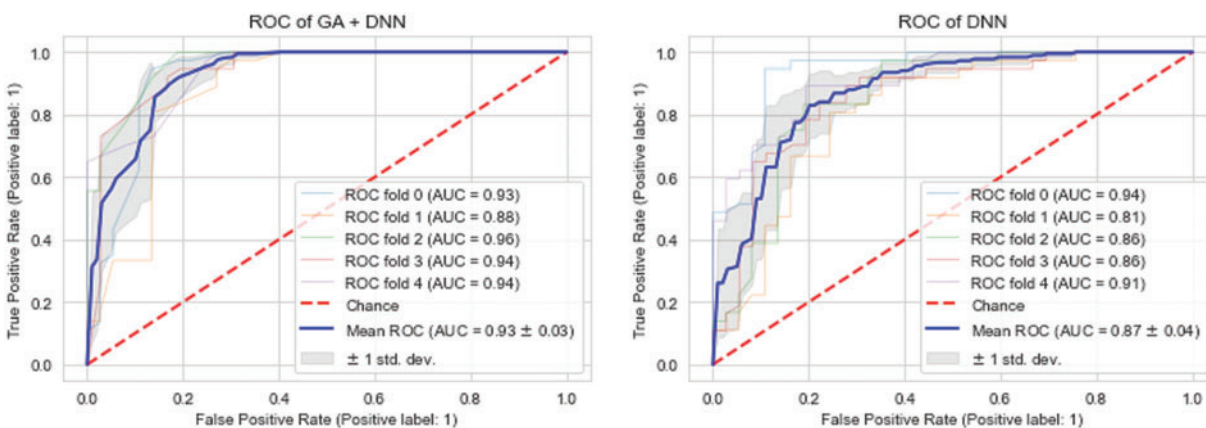
Figure 4: ROC comparison of proposed model (GA_DNN) against traditional DNN model

6.3 Experiment No. 3: Results of Other State-of-the-Art Machine Learning Models

In this section, we have compared the performance of proposed models against the other state-of-the-art ML models while using same dementia dataset. Naive bayes (NB), Logistic regression (LR), random forest (RF) classifier, decision tree (DT) classifier, k-nearest neighbor (kNN), Adaboost ensemble classifier, support vector machine (SVM) with radial basis function (RBF) kernel, and linear SVM were considered for performance comparison.

For fair performance comparison with the proposed models, each ML model used GA for feature selection from the dataset. Table 5 shows the results of the above-mentioned models along with the

feature selected (F$_S$) by GA and evaluation metrics. From the Table 5 it can be observed that the newly proposed model obtained the highest accuracy, 93.15%, while using 09 features from the dataset. On the other hand, LR, DT, RF, SVM (linear) and Adaboost models achieved lower accuracies while only using a single feature from the dataset.

Table 5: Results of several feature subsets for the dementia disease dataset based on state-of-art ML models using GA for feature selection where Hyper: hyperparameter values of ML model, FS: feature selected by GA, Acc._Train: Accuracy on training-data, Acc._Test: Accuracy on testing-data, Sens.: Sensitivity, Spec.: Specificity

Model	Hyper.	F$_S$	Acc._Train	Acc._Test	Sens.	Spec.
GA + NB	$V = 0.75$	03, 24, 40, 66, 74	85.65	88.90	92.75	86.51
GA + LR	$C = 05$	52	89.25	86.23	81.69	88.34
GA + DT	$Ne = 10$	52	78.11	87.55	84.82	89.12
GA + RF	$Ne = 50$	52	80.44	85.50	86.52	81.22
GA + kNN	$K = 14$	39, 52, 62, 68	89.19	86.00	78.86	88.16
GA + SVM (lin)	$C = 0.5$	52	85.00	86.23	90.55	82.15
GA + SVM (brf)	$C = 1.0$	1, 7, 13, 31, 44, 58, 70, 73, 75	71.25	74.31	64.23	73.74
GA + Adaboost	$Ne = 10$	03	80.00	78.80	82.50	77.91
GA + ANN	$Eg = 08$	0, 03, 06, 40, 41, 54, 65	85.95	90.36	92.81	89.79
Proposed (GA + DNN)	$Eg = 10$	03, 17, 23, 27, 36, 40, 55, 57, 75	90.36	93.15	95.75	91.59

7 Discussion

In this paper, we proposed a method for the 10-year multifactorial prediction of dementia composed of a feature selection module based on GA and a classification module based on DNN. This approach took into consideration 75 features from multiple domains (lifestyle, demographic, social, health history, biochemical tests, physical assessment, psychological examination and other health tools). The importance of such prediction is highlighted by the importance of risk reduction in a timely manner in regards to dementia which is important since there is a consensus that dementia is a multifactorial disorder [2]. The proposed method achieved an accuracy of 93.36%, sensitivity of 93.15%, specificity of 91.59% and MCC of 0.4788, and performed superior to 11 recently proposed ML models by the researchers for dementia prediction.

The selected features given by the best model of the proposed method, to predict dementia in a 10 years timespan, were: age, past smoking habit, history of infarct, history of TIA/RIND, Depression, Hip fracture, single leg standing test with right leg and score in the Physical Component Summary (PCS-12 [30]). These will be discussed in the following. Not surprisingly, age was selected by the feature selection algorithm, which is a known and established major risk for dementia. It is reported in the literature that there is an increased risk for individuals older than 65 years, which is responsible for 95% of the cases [2]. The selected lifestyle features comprised past smoking habits and the physical status. Smoking is an established risk for dementia with studies reporting an accelerated cognitive decline in mid and late-life smokers in comparison to non-smokers [31], measured by the Mini-Mental State Examination score [32]. The physical health status of an individual given by the PCS-12 score is

related to physical activity, strength, pain etc. Kivipelto et al. [33], in an analysis of the results from lifestyle interventions from diverse dementia clinical trials, points out physical activity as an important factor in prevention efforts. A poor score on the single leg standing test could also be related to frailty and physical strength, which are risk factors for dementia [2]. The medical history of infarct and TIA/RIND could be related to vascular risk factors, which can induce cognitive impairment through both structural and functional damage inflicted on cerebral blood vessels [34]. Damage to the cerebrovascular system can lead to vascular dementia and Alzheimer's disease. Other vascular risks like persistent hypertension between 40 and 50 years are shown to increase the risk of cognitive impairment 20 years later [35].

The correlation between depression and dementia is complex because of the diagnostic confusion of pseudo-dementia. Pseudo-dementia is a term referring to cases where a psychiatric disorder happens mimicking common symptoms of dementia in older people, such as deficits in memory, executive function, speech and language [36]. However, a review of evidence on this topic revealed that chronic major depression is often a prequel to dementia, and they share pathological features like increased neurodegeneration, and reduced neuroprotection and repair [37]. Hip fracture is a common occurrence among individuals who present with cognitive impairment and dementia conditions. A review on this topic, which included 36 studies, estimated a prevalence of 41.8% and 19.2% in individuals with cognitive impairment and dementia, respectively [38]. In terms of dementia risk for hip fracture patients, it is speculated that the complications that follow hip fracture surgery can increase this risk, e.g., reduced physical activity and postoperative delirium [39]. Olofsson et al. [40] reported, in a 3-year follow-up study on postoperative delirium, that 31.8% of the participants developed dementia.

From the features chosen by the proposed method and which provided the best predictive model for dementia in 10 years, it is possible to identify modifiable factors, which are possible to act upon. Encouraging individuals to stop smoking and engage in physical exercise is already part of medical advice for a healthy life, which prevents a series of negative health outcomes. Regarding the acting on vascular risk factors, the literature diverges on the preventive effect of antihypertensive treatment on cognitive impairment [41,42]. Recent reviews also recommend that depression and depressive symptoms should be added to efforts for the prevention of dementia and cognitive decline [43]. Sun et al. presented a supervised learning model for extracting the relation between the features through lexicalized dependency [44]. They also presented active learning for relation extraction [45]. Furthermore, we compared the outcomes of the newly presented model to previous cutting-edge ML models offered by the scientists for dementia prediction. The proposed model obtained much superior outcomes when compared to previous proposed ML models, as shown in Table 6.

Table 6: Comparison of classification accuracies with previously presented ML approaches for dementia prediction

Study_Year	Method	Accuracy (%)	Balancing
Po-Chuan et al. (2012) [46]	PNNs	83.00	No
Gurevich et al. (2017) [47]	SVM	89.00	Yes
Stamate et al. (2018) [48]	Gradient Boosting	88.00	Yes
Visser et al. (2019) [49]	XGBoost + RF	88.00	No
Dallora et al. (2020) [50]	DT	74.50	Yes
Karaglani et al. (2020) [51]	RF	84.60	No

(Continued)

Table 6: Continued

Study_Year	Method	Accuracy (%)	Balancing
Ryzhikova et al. (2021) [52]	ANN + SVM	84.00	No
Salem et al. (2021) [53]	RF	88.00	Yes
Garcia-Gutierrez et.al. (2022) [54]	GA	84.00	No
Shahzad et al. (2022) [55]	SVM	71.7	No
Javeed et al. (2022) [56]	Autoencoder + Adaboost	90.23	Yes
Proposed Model (2022)	GA + DNN	93.15	Yes

8 Conclusion and Future Works

Dementia is a syndrome with a large social effect and severe repercussions for its victims, who experience gradual cognitive deterioration that leads to increased morbidity, mortality, and impairments. Because it is known that dementia is a complex condition that manifests alterations in the brain of the affected individual as early as 15 years before its beginning, prediction models aimed at its early diagnosis and risk identification should take these characteristics into account. The work presented herein proposes a model for the multifactorial prediction of dementia in 10 years based on a GA feature selection module and a DNN classification module. The proposed method achieved an accuracy of 93.36%, sensitivity of 93.15%, specificity of 91.59% and MCC of 0.4788. This prediction took into consideration a range of changeable and non-changeable features and identified age, past smoking habit, history of infarct, history of TIA/RIND, depression, hip fracture, single leg standing test with right leg and score in the Physical Component Summary (PCS-12) as the best predictors. The identification of risk factors that are possible to be acted upon opens possibilities to delay or even avoid the onset of dementia. Future work will rely on testing the proposed method in other SNAC databases.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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