Hindawi
Journal of Food Quality
Volume 2024, Article ID 9826910, 1 page
https://doi.org/10.1155/2024/9826910

Retraction

Retracted: Machine Learning Model-Based Applications for Food Management in Alzheimer's Using Regression Analysis Approach

Journal of Food Quality

Received 23 January 2024; Accepted 23 January 2024; Published 24 January 2024

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] S. H. Kumhar, P. R. Kapula, H. Kaur et al., "Machine Learning Model-Based Applications for Food Management in Alzheimer's Using Regression Analysis Approach," *Journal of Food Quality*, vol. 2022, Article ID 1519451, 12 pages, 2022.

Hindawi
Journal of Food Quality
Volume 2022, Article ID 1519451, 12 pages
https://doi.org/10.1155/2022/1519451

WILEY | Hindawi

Research Article

Machine Learning Model-Based Applications for Food Management in Alzheimer's Using Regression Analysis Approach

Sajadul Hassan Kumhar,[1] **Prabhakara Rao Kapula**,[2] **Harveen Kaur**,[3] **Radeep R. Krishna**,[4] **Mudasir M Kirmani**,[5] **Vijay Anant Athavale**,[6] **and Mohd Wazih Ahmad**[7]

[1]*Department of Computer Science, Sri Satya Sai University of Technology and Medical Science, Sehore, India*
[2]*Department of ECE, B V Raju Institute of Technology, Narsapur, Telangana, India*
[3]*Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab, India*
[4]*Department of ECE, Mangalam College of Engineering, Ettumanoor, Kerala, India*
[5]*Department of Social Science, FoFy, SKUAST-Kashmir, Srinagar, India*
[6]*Walchand Institute of Technology, Solapur, Maharashtra, India*
[7]*Adama Science and Technology University, Adama, Ethiopia*

Correspondence should be addressed to Mohd Wazih Ahmad; wazih.ahmad@astu.edu.et

Received 31 March 2022; Revised 24 April 2022; Accepted 27 April 2022; Published 19 May 2022

Academic Editor: Rijwan Khan

Alzheimer's disease (AD) has become a public health concern due to its misinterpretation with vascular dementia (VD) and mixed dementia Alzheimer's disease (MXD). Therefore, an accurate differentiation of these diseases is essential for improving the treatment procedure. It has been seen that nutrition along with several other factors plays a role in the disease progression. Scientists are trying to find a solution using some machine learning (ML) techniques. The ML algorithms used for this purpose are neural networks, support vector machines, regression and many more. The current research is focused on understanding the extent of the application of machine learning tools in enhancing food management for patients with Alzheimer's since there is no cure known for the same. A total of 100 patient data have been collected where the patients had AD, VD, and MXD. Their demographic data, dietary intake, Fazekas scores, and Hachinski scores were collected (independent variables) and analysed in IBM SPSS by considering the risk of development of AD, VD, and MXD as dependent variables. The findings showed that age is highly related ($p < 0.001$) to the development of these three diseases and other demographics are not prioritized. Discussion of other available journal articles showed that nutritional intake, Fazekas scores, Hachinski scores, and gender are also indicators for predicting these diseases ($p < 0.001$). Thus, this study concluded that age, gender, diet consumption, and Fazekas and Hachinski scores are important indicators for differentiating AD from other diseases, and ML can be used to create a custom nutrition plan based on the patient's diet and stage of disease progression. Lastly, future scopes of ML have been explained in this paper.

1. Introduction

The current medical treatment for several incurable diseases relies mainly on food and medication for prevention, treatment, and speedy recovery of the patients and in certain cases favoured over other treatments. Chronic diseases like diabetes, thyroid, and other ailments focus on providing food as the key source of treatment for individuals to successfully overcome the diseases and lead a healthy and happy life [1–3]. Alzheimer's disease, often recognized as AD, is a prevalent type of dementia in the elderly. The main cause of AD is amyloid beta plaque accumulation, which ultimately leads to a neurodegenerative disorder. Some areas of the brain, such as mesial, temporal, and prefrontal areas are affected by this disease, which ultimately develop dementia symptoms. The primary association of dementia in AD is severe cognitive degradation and dysfunction of memory [4]. These are the results of tissue shrinkage inside the brain. Concerning this, NHS UK states that AD is caused by the accumulation of proteins such as amyloid and tau, which ultimately develop plaques and tangles, respectively, inside the brain [5]. Scientists are still searching for the cause which results in the accumulation of these substances inside the brain. Accumulation of these substances lowers the transmitting signals by preventing acetylcholine from reaching its destined neurons. Ultimately, it develops neurodegenerative disorders and cognitive impairment [6].

Scientists and clinicians are trying to find a solution in using food management as the critical aspect in managing AD in an effective manner, for this purpose they need more data and information about the patients' health conditions which would enable in overcoming the issues in an effective manner for accurate diagnosis of AD because any cerebrovascular change and symptoms of "vascular dementia" (VD) resemble the symptoms of AD [7]. Moreover, VD is as frequent as AD as well, which also makes it difficult to diagnose properly. The mechanism of AD has already been mentioned; whereas, VD causes cognitive dysfunction and tissue damage inside the brain. Clinicians use "Magnetic Resonance Imaging" or MR images to classify and differentiate these two diseases among elderly individuals [8]. In that scenario, Functional-MRI or fMRI and "Diffusion Tensor Imaging" or DTI are also used for accurate detection [9]. Scientists found that VD and AD are characterized by different patterns of "white matter" of the brain. These have been classified by using DTI parameters. Apart from this, fMRI images are being used to characterize the "Functional Connectivity" of the brain, which has shown promising diagnosis insights in the AD and VD pathophysiology. Although these biomarkers and pathophysiological signs are important parameters for diagnosing these diseases, clinicians still find it difficult to diagnose AD accurately.

Nowadays, machine learning (ML) has become an interesting tool to diagnose a disease and predict its future outcomes. Therefore, developers are focusing on its improvement for the accurate diagnosis of AD by taking images from quantitative MRI (qMRI) [10]. Diagnosis of AD using the combination of qMRI and ML showed promising benefits in automatic identification and predicting the progression of that disease.

Concerning the previous studies and their findings, this study is aiming to establish a differential analysis for accurate diagnosis of AD. As previously mentioned, VD is frequently misdiagnosed with that of AD; and thus, the differential analysis will help readers to understand whether the ML approaches bring any future hopes to accurately differentiate AD from VD. The researchers have used a regression analysis tool to accomplish the research goals and discussed the major findings. The present investigation is utilizing machine learning technique known as regression analysis to enhance differential analysis of Alzheimer's disease. The overall ML model showed a maximum of 98% accuracy with a maximum of 11% of standard error. The paper is focused on the implementation of machine learning approaches in the effective management of Alzheimer's via nutrition as proposed by ML considering different factors.

1.1. Organization. The paper is organized into different sections initiated with the Introduction section as part 1 followed by a second part as Literature review to uphold the past studies on ML and other Artificial Intelligence approaches for disease diagnosis like Alzheimer's and dietary studies performed with respect to Alzheimer's. Thereafter, Section 3 elucidates the research methodology followed by section 4 that states the analysis and interpretations. Part 5 defines the discussion and findings in available journal articles for a more accurate justification of the primary findings. Finally, section 6 states the conclusion by aggregating the major findings.

2. Literature Review

Alzheimer's disease or AD is becoming a serious concern in elderly people due to its inaccurate diagnosis. As a result, inaccurate treatment is getting observed in the healthcare sector. Thus, scientists are finding an alternative solution for improving diagnosis efficacy. Stamate and colleagues have used cerebrospinal fluid (CSF) as a biomarker for detecting AD in patients. They used different ML algorithms for identifying the disease class tuning ability [11]. Around 240 individuals have been selected where 113 were normal individuals with no cognitive disorder and the rest had AD dementia symptoms. Besides considering CSF as the biomarker for identifying AD, the authors used data of cognitive function and other clinical data. As previously mentioned, proteins such as amyloid and tau are responsible for developing AD in elderly individuals; thus, the authors have tested the levels of tau and amyloid for an effective diagnosis. Specific kinds of diets have been explored to evaluate the nutritional intake desired for a variety of disorders, especially Alzheimer's; however, this technique must be digitized to customise culinary regimens for each patient. Certain other ways are Mediterranean, Dash, and MIND which seem to be just a few of the regimens that have been investigated with regards to the prevention and rehabilitation of Alzheimer's disease. Other demographic data, such as gender and age have also been considered.

The comparison has been done among three ML algorithms, such as "random forest (RF)," "Deep Learning (DL)," and "XGBoost." The results showed that XGBoost can detect AD when metabolite biomarkers are used. Figure 1 shows the sensitivity and specificity of the 3 ML algorithms. AUC : Area under Curve and ROC defines "Receiver operating characteristic."

The findings from the above graph (Figure 1) suggest that the AUC of 0.97 of the entire model is 97% accurate when metabolites (Figure 2) are used for predicting AD. Below, Figure 2 shows the metabolite biomarkers used by the authors. *Y*-axis suggests the priority and importance of metabolites and the *X*-axis refers to their names.

Katako and coresearchers performed automated disease classification using PET images to identify AD and differentiate it from that of Parkinson's disease. Their study has shown that "Support Vector Machine" or SVM is providing the best results among other automated algorithms in identifying AD at the "prodromal stage" [12]. Moreover,

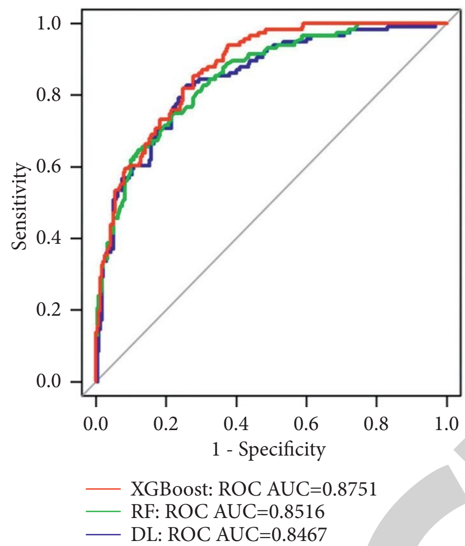


Figure 1: Accuracy [11].

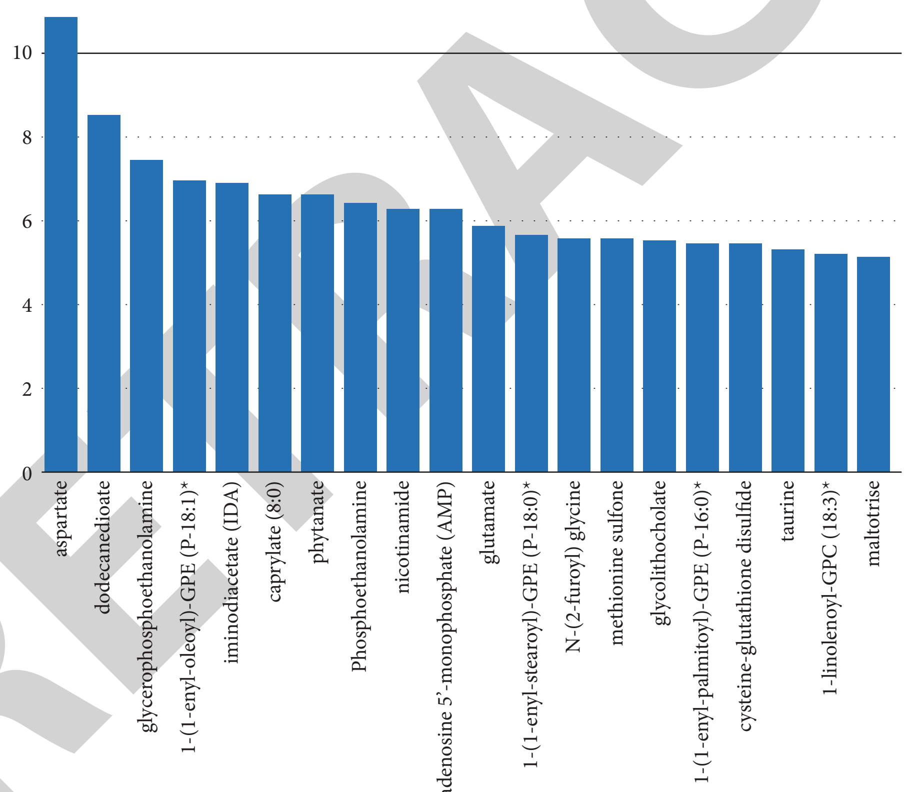


Figure 2: Metabolite biomarkers and their importance in ML algorithms for AD diagnosis [11].

their study on differential analysis showed that SVM can differentiate AD, Parkinson's disease, and dementia. The current research will also use the SVM algorithm for differentiating AD from that of VD and MXD. Chauhan has also performed differentiation of AD from other cognitive disorders using SVM. The author explained that AD is sometimes misdiagnosed with "mild cognitive impairment" (MCI) which is not a true AD; however, early and accurate diagnosis is still essential to prevent both of them [13]. Chauhan has used "Convolutional Neural Network" (CNN) and SVM for classifying AD and differentiating it from MCI. To perform the experiment, the algorithms were trained with a large number of training datasets from MRI [14]. A total of 300 patients with AD and MCI have been taken with 20 regular controls to generate a brain MRI dataset. The experimental flowchart by Chauhan [1] is shown in Figure 3.

The study showed an accuracy between 77 and 95% when both CNN and SVM were used. Chauhan did not identify the accuracy level of CNN and SVM individually. Overall, they found that the accuracy ranged from 77 to 95%. In this case, CNN is a deep learning (DL) algorithm and SVM is an ML algorithm [15]. The differences between these two algorithms are essential to select the best among them. Some studies stated that SVM is the best approach in classifying and differentiating AD. However, the study of the DL algorithm in classifying AD has not been explained yet in this literature. Ding and colleagues performed an experiment with DL for identifying and predicting AD using PET scan images [16]. Their study showed that DL algorithms had 57% sensitivity and 91% specificity with a significance value less than 0.05 ($p < 0.05$), which suggested that DL algorithms are effective in predicting AD. Their study showed that the diagnosis can be predicted before 75 months of the final diagnosis. As the current study is based on ML; thus, the literature will not uphold the explanation of DL later. Alzheimer's illness AD, vascular dementia (VD), and mixed dementia MXD are the three main ailments with similar symptoms such as thinking hurdles, delusion, remembrance and concentration issues etc., which have been envisaged using SVM, PET scans, etc. However in this study, an ML algorithm is being used. Asim and coresearchers have used SVM for classifying AD using ADNI (Alzheimer's disease neuroimaging initiative) database. They also differentiated AD with the MCI and cognitive normal (CN) results [17]. Their input image dataset is shown in Figure 4.

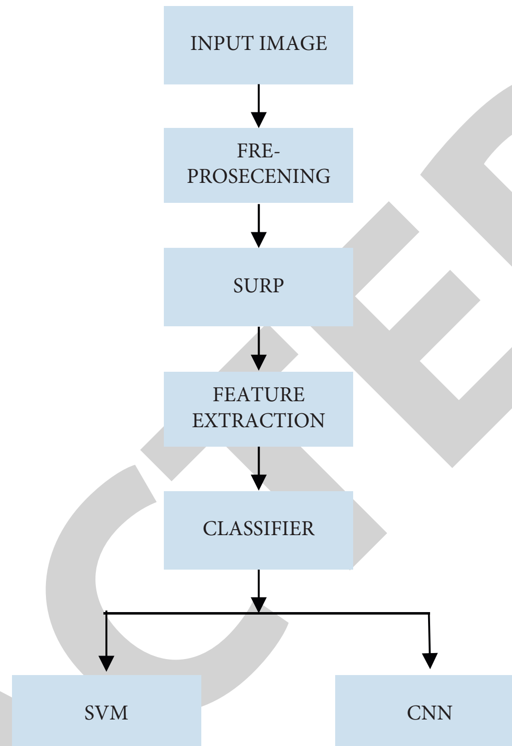


Figure 3: Experiment flow chart by Chauhan [11].

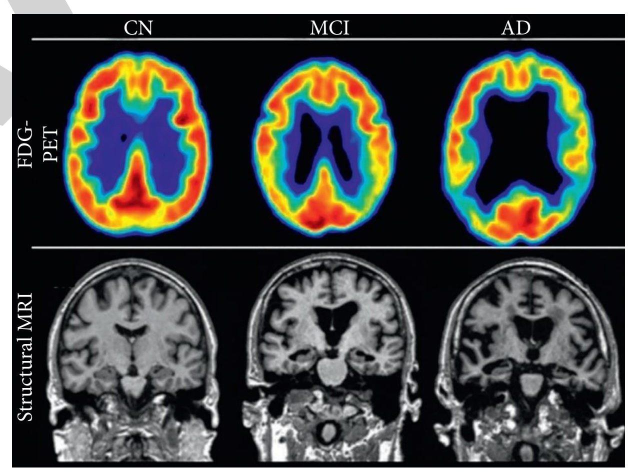


Figure 4: Input image dataset of Asim and coresearchers (FDG = fluorodeoxyglucose) [17].

The study has shown an accuracy of 94% when SVM algorithms were used. It is the highest accuracy obtained when AD was differentiated with CN. When they differentiated AD with MCI, the algorithm showed even more accuracy. This suggests that the SVM classification approach is highly beneficial and accurate in predicting and diagnosing AD. Moreover, SVM has shown to be accurate in differentiating AD from those of CN and MCI as well, which makes it an ideal and fine algorithm in AD prediction. In this context, DL did not show higher accuracy than ML. Therefore, ML, especially the SVM algorithm is the best for predicting AD. The current research is also using SVM for justifying the accuracy of the currently proposed method.

Abate and colleagues have experimented with ML algorithms for the early diagnosis of AD. These authors have also performed the differentiation analysis to differentiate between AD and MCI. The study shows that the authors have taken blood-based biomarkers for the identification of the risk of developing AD. Their study is slightly different from other studies. Other studies have identified the levels of biomarkers, metabolites, and two proteins. However, this study has studied a protein called p53. They observed the unfolded conformation of p53 (U-p53) in a blood plasma sample [18]. After observing the combination of unfolded-p53 with a respective antibody, 2D3A8, the risk of AD has been measured. The results showed an AUC of 0.92, which suggests a promising accuracy in the prediction and diagnosis of AD. Figure 5 shows the experimentation results where it can be observed that the levels of p53 remain constant throughout the lives of cognitively normal individuals. The level of U-p53 increases at a lower rate in MCI patients and the levels increase rapidly in individuals with a risk of AD. Therefore, when the rate of U-p53 can be measured in the blood sample, the risk of developing AD can be measured accurately by the ML algorithm.

Lazli and coworkers suggested employing ML and data mining techniques for envisaging AD by integrating a multimodal fusion approach with brain images which recommends that MRI provide high-quality resolution images compared to PET scans used traditionally. Moreover, MRI provides only anatomical information whereas PET provides functional information, thus experimentation with only MRI or PET may not bring an accurate classification [19].

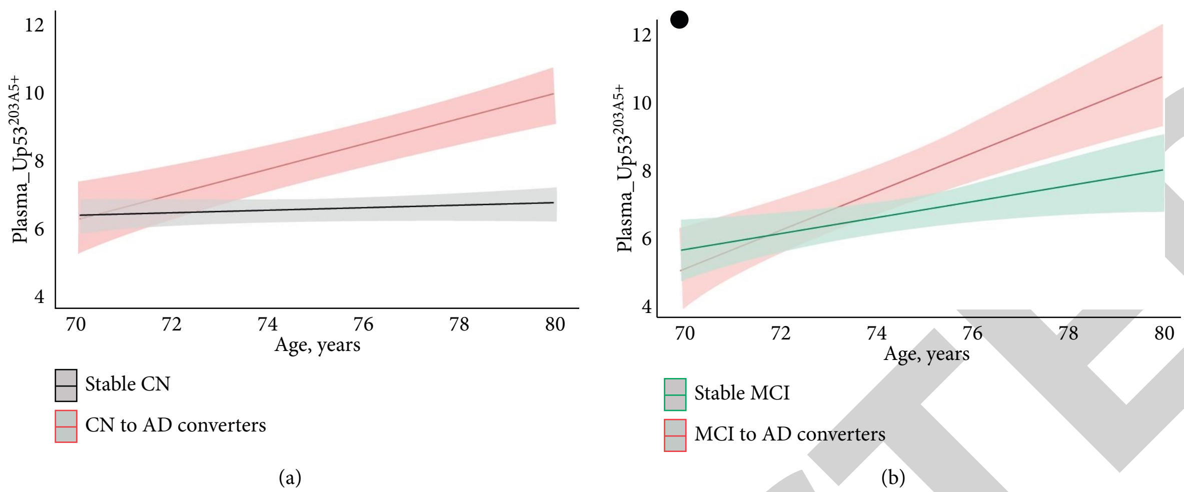


Figure 5: (a) Levels of unfolded-p53 increase with age, which promotes AD. (b) The level of U-p53 in stable MCI, where the levels of U-p53 do not increase as much as they increase in AD [18].

The combination of both image datasets by the multimodal image fusion technique will improve the accuracy of AD prediction.

Due to a lack of cure, nutrition, dietary patterns, and other factors have been studied extensively to understand their effect on disease progression. Different types of diets have been studied to determine the nutritious intake desired for several diseases including Alzheimer's, but there is a need to automate this process to customise the dietary plans for each patient. Mediterranean, Dash, and MIND are some of the diets that have been studied in correlation with AD prevention and treatment [20, 21]. Nutrition and dietary patterns can determine the probability of disease prevalence. Proper nutrition holds a key to leading a healthier life and can affect one's recovery from a disease [22, 23]. ML holds a key towards diet automation and has also been explored in this paper.

3. Research Methodology

Multiple linear regression analysis was used to examine the components and their implications to truly comprehend the characteristics that encourage the development of these three diseases that are considered in this work. Furthermore, the descriptive statistics values produced in the regression analysis have demonstrated a scenario in which both males and females have been considered to understand its prevalence and frequency on a gender basis. The acquisition of MRI images and their dietary plans has been performed on 100 individuals aged between 60 and 80. The range of ages has been considered for understanding whether age has any significant impact on the development of AD. A total of 35 individuals had AD, another 35 had VD, and the final 30 individuals had mixed AD-VD (MXD) dementia symptoms. These subjects have been taken to understand the factors that are mostly responsible for causing these three diseases. After analyzing the considerable factors for AD, VD, and MXD, the ML algorithm will be used to understand the accuracy of algorithms.

As this is a differential analysis, these three frequently occurring diseases have been taken to understand how to improve the accuracy of ML for differentiating them. The data from the preliminary analysis will uphold the factors that are essential for ML algorithms to consider first. After that, other factors can be considered. In this research, primary data have been collected and recorded in Microsoft Excel. The data include sex ratio, age education, memory, language, visuospatial skills, executive functions, and Fazekas and Hachinski scores. After analyzing the factors and their impact on the development of the three diseases, the final discussion will be drawn.

To analyse the factors and their impacts, multiple linear regression analysis has been carried out to understand the factors that are responsible for developing these three diseases. Moreover, the values of the descriptive statistics obtained in the regression analysis will allow the researchers to know their parameters and standard deviations that deviate from AD, VD, and MXD. Data from individual patients have been collected and recorded in Microsoft Excel. After that, IBM SPSS version 26 software has been used to accomplish linear regression analysis. The analysis will generate the coefficient, ANOVA, and significance values which will identify the crucial and noncrucial factors for an ML algorithm to consider for an accurate diagnosis of AD. Apart from this, the identified factors will also allow ML algorithms to differentiate between AD, VD, and MXD.

3.1. Variables for Regression Analysis

3.1.1. Independent. Sex, age (60–80), education (years), memory, language, visuospatial skills, executive functions, and Fazekas and Hachinski scores are the independent variables.

3.1.2. Dependent: Risk of Developing AD, VD, and MXD. After analyzing and generating the outputs, the ML algorithm will be fed to the dataset and the accuracy will be measured. In this condition, DTI, fMRI, and DTI + fMRI images have been considered as the datasets for the ML algorithm "Support Vector Machine" (SVM). The three types of datasets that contain individual DTI and fMRI images and the combined DTI + fMRI images will allow the researchers to know whether the accuracy is affected by using individual and combined scanned images. The accuracy will be compared by descriptive statistics and regression analysis using IBM SPSS.

After interpreting the outputs from the analysis, the research will move forward for drawing discussion. The discussion has been made using the findings from the primary analysis. Additionally, recently available journal articles (2018–2022) have been studied to understand the accuracy of the primary research. The recent journal articles will uphold the current study findings of ML and other Artificial Intelligence (AI) algorithms in Alzheimer's prediction. Figure 6 shows the flowchart for the research followed.

3.1.3. Research Questions.

What are the factors responsible for developing AD, VD, and MXD?

What are the crucial factors required for differentiating AD from that of VD and MXD?

Which neuroimaging technique is more accurate in classifying AD using ML (DTI, fMRI, or DTI + fMRI technique)?

Which ML algorithm is the most accurate in classifying AD?

What kind of dietary changes are needed to improve quality of life in AD patients?

4. Analysis and Interpretation

The regression analysis has been carried out in IBM SPSS where the relationships have been considered statistically significant at $p < 0.05$ value. Below, the tabulated output data have been represented for further interpretation. A total of three dependent variables were selected and the impact of independent variables on them has been analysed.

Table 1 depicts the impact of independent variables on the risk of developing AD. It has been observed that sex is not statistically significant in developing AD. However, there is a relationship between sex and developing AD. As the t value shows −1.213, this suggests that females are more prone to developing AD than males. In the analysis, 1 = female and 2 = male have been considered. Age has shown itself to be completely significant in developing AD. Other independent variables, such as education, memory, language, visuospatial skills, and executive functions did not show any statistically significant relationship with AD development. However, the Fazekas and Hachinski scores are slightly confusing here. The relationship showed no statistical significance; however, the standard error is significantly higher for these two scores (2.658 and 2.743, respectively). Fazekas and Hachinski scores are essential indicators for determining the likelihood of developing AD as well as other neurodegenerative ailments and suggest that these two independent correlation scores have potential importance in the development of AD; however, due to the lack of effective analysis, probably, the statistical significance did not appear. Below, Figure 7 shows that Fazekas and Hachinski scores increase with the risk of developing these diseases.

Table 2 shows similar results to that of Table 1, where it can be observed that age is statistically significant in the risk of developing VD. Other factors, such as gender and other independent variables are also not statistically significant. Gender, in this case, is also negatively related (−0.1427) to VD which suggests that females are more prone to developing VD. In this analysis, Fazekas and Hachinski scores also represent a higher standard error value, which suggests that the analysis is not truly acceptable for these two scores. Apparently, Figure 7 suggests that these two scores are increased when the risk of AD and VD are observed.

Similar cases have been observed in Table 3 as well. In this context, Fazekas and Hachinski scores show the maximum standard error. Therefore, the two scores are highly dependent on the MXD development despite nonstatistical significance of it. Age is also responsible for developing MXD ($p < 0.02$). In this scenario, gender has shown a positive t value, which suggests that males are more prone to MXD than females. Other independent variables are not statistically significant in developing MXD and thus, the factors are not given priority.

Table 4 shows the R square as well as the accuracy of the current model. The adjusted R square value ranges between 0.932 and 0.984, which suggests that the accuracy of the current model is 93.2–98.4%.

Table 5 shows that the minimum Fazekas and Hachinski scores observed were 0.8 and the maximum scores observed were 2.6 and 2.7, respectively.

The three graphs A, B, and C are not skewed to the right or left direction, which suggests that the values are symmetrically interchangeable. This has been shown in Figure 8. The essential indicators for determining the likelihood of developing Alzheimer's disease are age, Fazekas, and Hachinski scores which are three important factors for consideration to understand the risk of developing AD, VD, and MXD.

5. Discussion and Findings

The analysis and interpretation found that age and diet were highly responsible for developing the three diseases. Fazekas and Hachinski's scores were not statistically significant for AD, VD, and MXD; however, Figure 7 and the standard error suggested that those values are also variable in patients with AD, VD, and MXD. A study by Castellazzi and colleagues showed that gender, Fazekas, and Hachinski values are statistically significant for AD, VD, and MXD. Another study by Podcasy and Epperson showed that males are at higher risk of developing vascular dementia or VD, whereas the current study has shown females are at higher risk of developing VD [24]. Although the results were not statistically significant and the t value was not highly acceptable

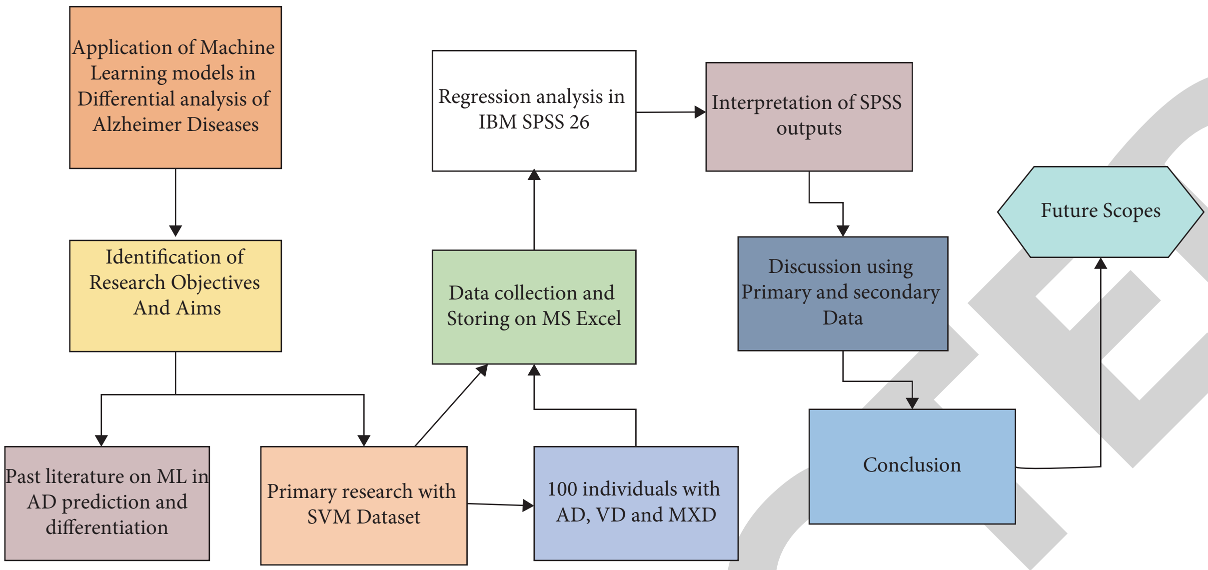


Figure 6: Flow chart of the research.

Table 1: Coefficient values for AD.

Model		Coefficients[a] Nonstandardized coefficients Std. error	t	Sig.
1	(Constant)	8.515	1.375	0.199
	Sex	0.798	−1.213	0.253
	Age	0.153	5.922	0.000
	Education (years)	0.133	−0.341	0.740
	Memory	1.111	−1.071	0.309
	Language	0.343	−0.877	0.401
	Visuospatial skills,	0.600	1.379	0.198
	Executive functions	1.394	−0.452	0.661
	Fazekas score	2.658	0.612	0.554
	Hachinski score	2.743	−0.072	0.944

a. Dependent Variable: Risk of AD.

(<2), the discussion could be moved forward to justify that males are at a higher risk of developing VD [25]. On the other hand, researchers have observed that females are at higher risk of developing AD [26]. This has been matched with the current study where it has been observed that females are at a higher risk of developing AD [27]. Therefore, the ML algorithms are required to prioritize gender for differentiating AD as gender has a crucial role in developing AD and VD [28].

The analysis and interpretation showed that the Fazekas score has a significant relationship with the development of risk. Although the results showed no statistical significance; however, due to high standard error, a significant relationship has been considered in the past study, but however, in the current work, ML algorithms are required to be trained effectively on WMC data, Hachinski scores, Fazekas scores, dietary requirements, and other essential demographic values for executing differential analysis [29]. A study by Kao and coworkers showed that white matter changes are related to developing the chance of dementia ($p < 0.05$). More specifically, patients with advanced dementia stages have shown periventricular white matter changes [30]. On the other hand, the white matter change is related to the Fazekas score. Therefore, ML needs to consider the Fazekas score besides other demographic data for the effective classification of Alzheimer's disease. However, this finding does not signify the differentiation analysis [31]. To accomplish the differential analysis, Fazekas scores for AD, VD, and MXD are required to be considered. The white matter changes (WMC) have been shown in Figure 9.

The current analysis has developed a Microsoft Excel sheet where it was observed that persons with AD had Fazekas scores around 1.5–3; persons with VD had Fazekas scores between 3.5 and 2; and MXD individuals had Fazekas scores between 2.1 and 6.1. Another study by Castellazzi and colleagues also showed similar results [32]. Moreover, their results showed Fazekas and Hachinski scores are statistically significant ($p < 0.001$) in developing AD, VD, and MXD, whereas the current study showed no statistical significance ($p > 0.5$) [31]. As these two analyses had a great amount of standard error (>2); thus, the $p$value has been neglected and it can be interpreted that the Hachinski score also has a

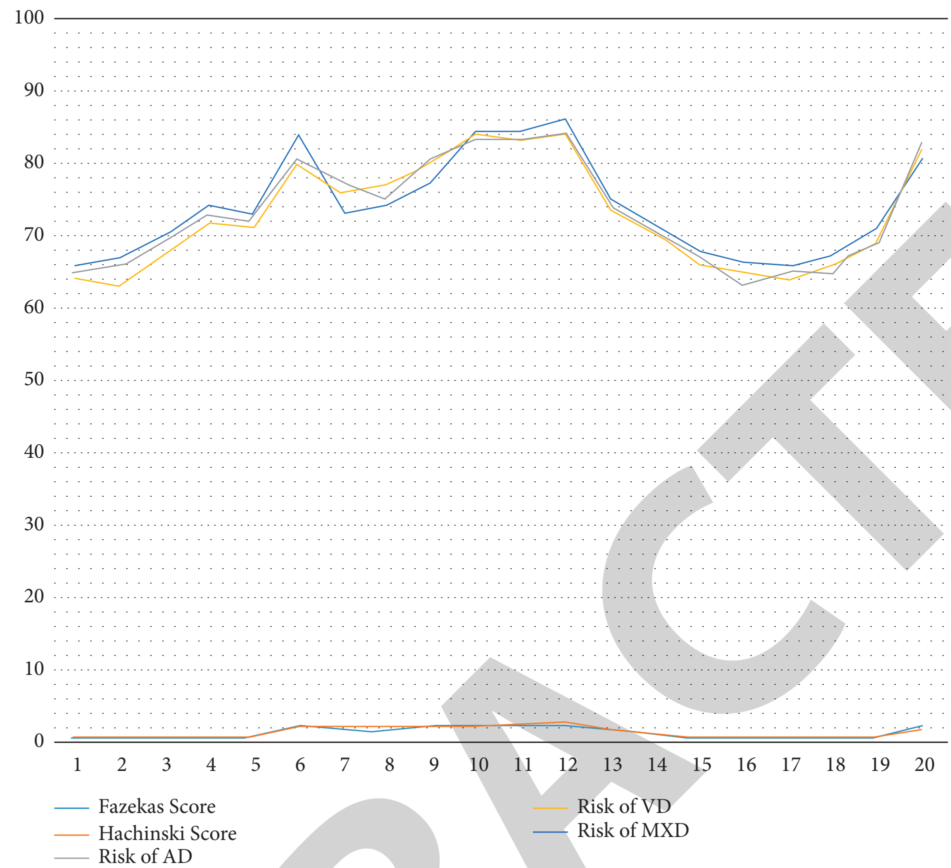


Figure 7: Changes in risk of AD, VD, and MXD development with Fazekas and Hachinski scores.

Table 2: Coefficient values for VD.

Model		Coefficients[a] Nonstandardized coefficients Std. error	t	Sig.
1	(Constant)	6.909	1.588	0.143
	Sex	0.648	−1.427	0.184
	Age	0.124	7.474	0.000
	Education (years)	0.108	−1.621	0.136
	Memory	0.901	2.093	0.063
	Language	0.278	−0.032	0.975
	Visuospatial skills,	0.486	0.522	0.613
	Executive functions	1.132	−1.569	0.148
	Fazekas score	2.156	0.642	0.535
	Hachinski score	2.226	−0.151	0.883

a. Dependent Variable: Risk of VD.

significant relationship with the development of abnormalities [33, 34]. Therefore, ML algorithms are required to be trained effectively with WMC data, Hachinski scores, Fazekas scores, dietary requirements, and other essential demographic values for executing differential analysis [35, 36]. The prevailing machine learning model, which is primarily incorporating logistic regression, seems to have a maximum accuracy of 98.4% and a minimum accuracy of 93.2%. The standard error spans from 9.16 percent to 11.29 percent, which is pretty large and needs constant attention. Since there are only 100 patients in the sample set, the error rate is likely larger, and the evaluation is less credible. As a result, a large number of datasets can improve the application of machine learning infrastructure. Additionally, SVM and neural networks can be utilized to enhance Alzheimer's disease differential analysis. The overall ML model showed a maximum of 98% accuracy with a maximum of 11% standard error.

Table 3: Coefficient values for MXD.

Model		Coefficients[a] Non standardized coefficients Std. error	t	Sig.
1	(Constant)	13.295	1.409	0.189
	Sex	1.246	1.455	0.176
	Age	0.238	2.855	0.017
	Education (years)	0.208	1.213	0.253
	Memory	1.735	−1.823	0.098
	Language	0.536	0.229	0.823
	Visuospatial skills,	0.936	−0.748	0.472
	Executive functions	2.177	1.054	0.317
	Fazekas score	4.149	−1.385	0.196
	Hachinski score	4.282	1.809	0.101

a. Dependent Variable: Risk of MXD.

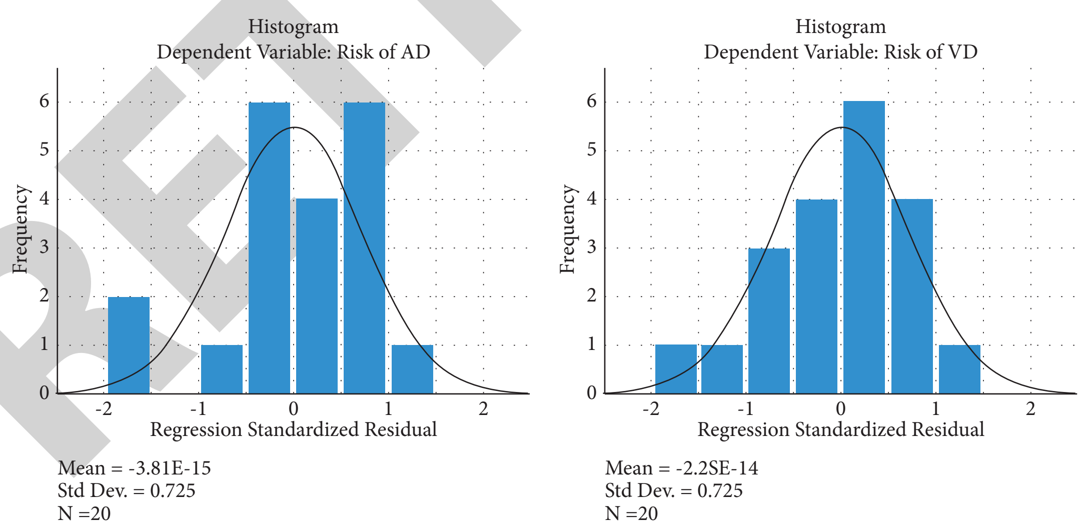
Table 4: Model summary of the entire analysis showing adjusted R square and standard error values.

Model summary[b]				
Model	R	R square	Adjusted R square	Std. error of the estimate
1	0.982–0.996[a]	0.964–0.992	0.932–0.984	0.916–1.129

a. Predictors: (Constant), Hachinski score, education (years), language, visuospatial skills, memory, sex, executive functions, age, Fazekasscore. b. Dependent variable: risk of AD, VD, and MXD.

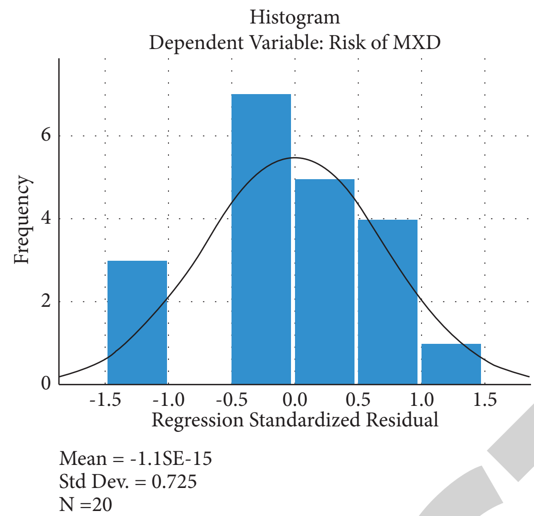
Table 5: Descriptive statistics showing the minimum and maximum scores of the primary input data.

Statistics	Sex	Age	Education (years)	Memory	Language	Visuospatial skills,	Executive functions	Fazekas score	Hachinski score
Minimum	1	60	2	0.00	1	1.00	0.800	0.8	0.8
Maximum	2	80	12	0.90	4	2.12	2.000	2.6	2.7



(a) (b)

Figure 8: Continued.



(c)

Figure 8: Residual statistics showing the graphs A B, and C are not skewed in any direction for AD, VD, and MXD.

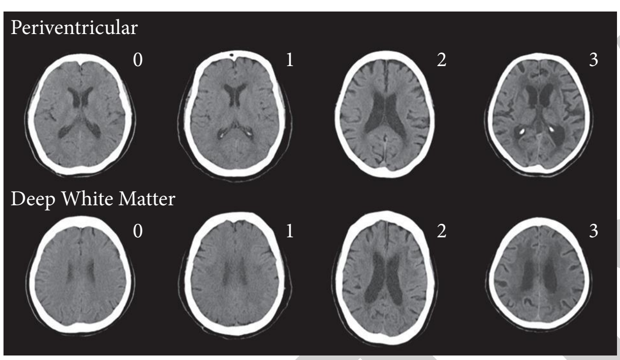


Figure 9: WMC in AD patients with Fazekas scale [30].

6. Conclusion

To facilitate differential analysis of Alzheimer's disease and produce the most suitable meal plan, the current study used a machine learning approach known as linear regression analysis. A total of 100 patient data have been collected and their demographic data, Fazekas scores, and Hachinski scores were extracted. The data were then stored in Microsoft Excel and then linear regression analysis was carried out in IBM SPSS software. Results showed that age and dietary habits have a significant impact on the development of AD, vascular dementia, and mixed AD-VD. Identification of these is not enough to facilitate differential analysis. Therefore, individual scores were analysed and differences in scores were observed that were needed to be considered for ML architecture training. Other studies also showed that Fazekas and Hachinski scores are essential for a differential analysis of ML. The overall ML model showed a maximum of 98% accuracy with a maximum of 11% standard error. Therefore, further research is required with a large amount of dataset to decrease the standard error.

7. Future Scope

The advancement of conventional ML algorithms brings a future prospect in image fusion and medical image recognition. The ML algorithms show an improved accuracy in image classification and differentiation during an image fusion technique. To simplify, MRI and PET images or MRI and computed tomography (CT) images are fused and trained with the ML algorithm for improving accuracy. Studies suggest that SVM, neural networks, and other ML architectures demand highly skilled expertise for their operation. Therefore, before its complete implementation, a training programme is essential for obtaining a significant benefit in the field of ML. Moreover, the food recommendation by the ML algorithm for AD might not be accurate enough and needs to be justified by the clinician before processing the treatment. Other future scopes of ML algorithms include short imaging times. Using ML can minimize the time of image processing and it will reduce the time consumption for disease detection and prediction. Among the ML algorithms, CNN has shown promising advantages in disease differentiation.

Data Availability

The data are available on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] S. Downer, S. A. Berkowitz, T. S. Harlan, D. L. Olstad, and D. Mozaffarian, "Food is medicine: actions to integrate food and nutrition into healthcare," *BMJ*, vol. 369, 2020.

[2] D. Mafra, N. A. Borges, B. Lindholm, P. G. Shiels, P. Evenepoel, and P. Stenvinkel, "Food as medicine: targeting

the uraemic phenotype in chronic kidney disease," *Nature Reviews Nephrology*, vol. 17, no. 3, pp. 153–171, 2021.

[3] F. L. Greenway, "Food as medicine for chronic disease: a strategy to address non-compliance," *Journal of Medicinal Food*, vol. 23, no. 9, pp. 903-904, 2020.

[4] G. Castellazzi, M. G. Cuzzoni, M. Cotta Ramusino et al., "A machine learning approach for the differential diagnosis of alzheimer and vascular dementia fed by MRI selected features," *Frontiers in Neuroinformatics*, vol. 14, p. 25, 2020.

[5] Nhs.uk, "Alzheimer's disease is thought to be caused by the abnormal build-up of proteins in and around brain cells," 2022, https://www.nhs.uk/conditions/alzheimers-disease/causes/#:%7E:text=Alzheimer's%20disease%20is%20thought%20to,form%20tangles%20within%20brain%20cells.

[6] M. Kivipelto, F. Mangialasche, and T. Ngandu, "Lifestyle interventions to prevent cognitive impairment, dementia and Alzheimer disease," *Nature Reviews Neurology*, vol. 14, no. 11, pp. 653–666, 2018.

[7] C. Tiel, F. K. Sudo, and A. B. Calmon, "Neuropsychiatric symptoms and executive function impairments in Alzheimer's disease and vascular dementia: the role of subcortical circuits," *Dementia & Neuropsychologia*, vol. 13, no. 3, pp. 293–298, 2019.

[8] A. Damulina, L. Pirpamer, M. Soellradl et al., "Cross-sectional and longitudinal assessment of brain iron level in Alzheimer disease using 3-T MRI," *Radiology*, vol. 296, no. 3, pp. 619–626, 2020.

[9] R. Marchitelli, M. Aiello, A. Cachia et al., "Simultaneous resting-state FDG-PET/fMRI in Alzheimer disease: relationship between glucose metabolism and intrinsic activity," *NeuroImage*, vol. 176, pp. 246–258, 2018.

[10] M. J. Knight, A. Wearn, E. Coulthard, and R. A. Kauppinen, "T2 Relaxometry and diffusion tensor indices of the hippocampus and entorhinal cortex improve sensitivity and specificity of MRI to detect amnestic mild cognitive impairment and Alzheimer's disease dementia," *Journal of Magnetic Resonance Imaging*, vol. 49, no. 2, pp. 445–455, 2019.

[11] D. S. Ushakov, V. V. Shepelev, and O. Y. Patlasov, "Innovative technologies of modified starch production," *IOP Conference Series: Earth and Environmental Science*, vol. 488, no. 1, Article ID 012032, 2020.

[12] D. Stamate, M. Kim, P. Proitsi et al., "A metabolite-based machine learning approach to diagnose Alzheimer-type dementia in blood: results from the European medical information framework for Alzheimer disease biomarker discovery cohort," *Alzheimer's and Dementia: Translational Research & Clinical Interventions*, vol. 5, no. 1, pp. 933–938, 2019.

[13] A. Katako, P. Shelton, A. L. Goertzen et al., "Machine learning identified an Alzheimer's disease-related FDG-PET pattern which is also expressed in Lewy body dementia and Parkinson's disease dementia," *Scientific Reports*, vol. 8, no. 1, pp. 1–3, 2018.

[14] J. S. Chauhan, "A review on support vector machine based classification of Alzheimer's disease from brain MRI," *International Journal of Scientific Research & Engineering Trends*, vol. 6, 2020.

[15] P. Sharma, Y. P. S. Berwal, and W. Ghai, "Performance analysis of deep learning CNN models for disease detection in plants using image segmentation," *Information Processing in Agriculture*, vol. 7, no. 4, pp. 566–574, 2020.

[16] Y. Ding, J. H. Sohn, M. G. Kawczynski et al., "A deep learning model to predict a diagnosis of Alzheimer disease by using 18F-FDG PET of the brain," *Radiology*, vol. 290, no. 2, pp. 456–464, 2019.

[17] Y. Asim, B. Raza, A. K. Malik, S. Rathore, L. Hussain, and M. A. Iftikhar, "A multi-modal, multi-atlas-based approach for Alzheimer detection via machine learning," *International Journal of Imaging Systems and Technology*, vol. 28, no. 2, pp. 113–123, 2018.

[18] K. Phasinam, T. Kassanuk, and M. Shabaz, "Applicability of internet of things in smart farming," *Journal of Food Quality*, vol. 2022, Article ID 7692922, 7 pages, 2022.

[19] G. Abate, M. Vezzoli, L. Polito et al., "A conformation variant of p53 combined with machine learning identifies Alzheimer disease in preclinical and prodromal stages," *Journal of Personalized Medicine*, vol. 11, no. 1, p. 14, 2021.

[20] D. Castillo-Barnes, L. Su, J. Ramírez et al., "Autosomal dominantly inherited alzheimer disease: analysis of genetic subgroups by machine learning," *Information Fusion*, vol. 58, pp. 153–167, 2020.

[21] A. Sharma, S. Kaur, N. Memon, A. Jainul Fathima, S. Ray, and M. W. Bhatt, "Alzheimer's patients detection using support vector machine (SVM) with quantitative analysis," *Neuroscience Informatics*, vol. 1, no. 3, Article ID 100012, 2021.

[22] S. Śliwińska and M. Jeziorek, "The role of nutrition in Alzheimer's disease," *Roczniki Panstwowego Zakladu Higieny*, vol. 72, pp. 29–39, 2021.

[23] P. Sharma, V. K. Gaur, and J. K. Srivastava, "Diet and nutrition in Alzheimer's disease and healthy aging," in *Biological, Diagnostic and Therapeutic Advances in Alzheimer's Disease*Springer, Berlin, Germany, 2019.

[24] A. S. Doorduijn, M. A. de van der Schueren, O. van de Rest et al., "Nutritional status is associated with clinical progression in Alzheimer's disease: the NUDAD Project," *Journal of the American Medical Directors Association*, vol. S1525, 2020.

[25] D. Ushakov, L. Cherkasova, and K. Shatila, "Environmental management system and its impact on productivity," *IOP Conference Series: Earth and Environmental Science*, vol. 937, no. 2, Article ID 022037, 2021.

[26] A. Popovac, A. Čelebić, S. Peršić, E. Stefanova, A. Milić Lemić, and I. Stančić, "Oral health status and nutritional habits as predictors for developing Alzheimer's disease," *Medical Principles and Practice*, vol. 30, no. 5, pp. 448–454, 2021.

[27] J. L. Podcasy and C. N. Epperson, "Considering sex and gender in Alzheimer disease and other dementias," *Dialogues in Clinical Neuroscience*, vol. 18, no. 4, pp. 437–446, 2016.

[28] B. Gulzar and A. Gupta, "DAM: a theoretical framework for sensor security in IoT applications," *International Journal of Next-Generation Computing*, vol. 12, no. 3, 2021.

[29] P. Ratta, A. Kaur, S. Sharma, M. Shabaz, and G. Dhiman, "Application of blockchain and internet of things in healthcare and medical sector: applications, challenges, and future perspectives," *Journal of Food Quality*, vol. 2021, Article ID 7608296, 20 pages, 2021.

[30] A. Gupta and L. K. Awasthi, *P4P: Ensuring Fault-Tolerance for Cycle-Stealing P2P Applications*GCA, Ahmedabad, India, 2007.

[31] C. Sharma, A. Bagga, R. Sobti, M. Shabaz, and R. Amin, "A robust image encrypted watermarking technique for neurodegenerative disorder diagnosis and its applications," *Computational and Mathematical Methods in Medicine*, vol. 2021, Article ID 8081276, 14 pages, 2021.

[32] A. Gupta and L. K. Awasthi, "Peer enterprises: possibilities, challenges and some ideas towards their realization," in *On the Move to Meaningful Internet Systems 2007: OTM 2007 Workshops*Springer, Berlin, Germany, 2007.

[33] Y.-H. Kao, M.-C. Chou, C.-H. Chen, and Y.-H. Yang, "White matter changes in patients with Alzheimer's disease and

associated factors," *Journal of Clinical Medicine*, vol. 8, no. 2, p. 167, 2019.

[34] C. Iadecola, M. Duering, V. Hachinski et al., "Vascular cognitive impairment and dementia," *Journal of the American College of Cardiology*, vol. 73, no. 25, pp. 3326–3344, 2019.

[35] J. Xie, Z. Cheng, L. Gu et al., "Evaluation of cerebrovascular hemodynamics in vascular dementia patients with a new individual computational fluid dynamics algorithm," *Computer Methods and Programs in Biomedicine*, vol. 213, Article ID 106497, 2022.

[36] S. Rodriguez, C. Hug, P. Todorov et al., "Machine learning identifies candidates for drug repurposing in Alzheimer's disease," *Nature Communications*, vol. 12, no. 1, pp. 1–3, 2021.