

Can Vascular Vertigo Be Recognized by Artificial Intelligence Methods?

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ABSTRACT

Introduction: The diversity of underlying causes poses a medical challenge in the differential diagnosis of dizziness. For many patients, the time to reach a diagnosis is quite long and includes several tests. This imposes a significant financial burden on the healthcare system while delaying the recognition and treatment of some neurological emergencies. In this paper, we present a machine learning-based method to aid in the early recognition of vascular causes of vertigo, which require timely management.

Methods: Using data such as age, gender, accompanying symptoms, comorbidities, and commonly known blood parameters, a machine learning-based preliminary evaluation method was designed to predict the most appropriate group for the patient. After identifying the effective features using statistical methods, various machine learning methods (decision tree, logistic regression, support vector machines, k-nearest neighbor, multilayer perceptron, and ensemble learning methods) were employed to determine dizziness groups.

Results: Experimental results present that age, serum albumin, presence of headache, hypertension and diabetes are crucial features to classify vascular vertigo patients. Accuracies range from 81.7% to 86% and the best result is achieved with the logistic regression method. The decision tree, support vector machines, k-nearest neighbor, multilayer perceptron, and ensemble methods reached accuracies of 83%, 85.5%, 84%, 81.7%, and 82.8%, respectively.

Conclusion: Our study provides reasonable evidence suggesting that machine learning models may be useful in predicting vascular vertigo cases before hospital admission. Further studies are needed to confirm these findings and improve accuracy. Our model may be beneficial for ambulance personnel, practitioners and for the specialists facing atypical and difficult cases of dizziness.

Keywords: Artificial intelligence, dizziness, machine learning, stroke, vertigo

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INTRODUCTION

Dizziness affects about 15-30% of people in the general population annually (1). It is one of the most frequent complaints encountered by family physicians, emergency doctors, neurologists and otorhinolaryngologists. It accounts for ~4% of all primary care and emergency room visits, and up to 30% in general neurology clinics (1), (2). Approximately 30-40% of adults experience clinically significant dizziness during their lifetime (3). Any sensation of disturbed spatial orientation is called dizziness (4). Patients use this term also for lightheadedness, disequilibrium, feeling faint or unsteadiness (5). *Vertigo* is a type of dizziness which is defined as an erroneous sense of motion. It is commonly described as environmental spinning or self-rotation (6). Dizziness may have various causes, including vestibular disorders, orthostatic hypotension, dehydration, medication side effects, mood disorders, anxiety, vitamin deficiencies or neurological conditions. Most of these causes are benign. Vertigo is a sign of peripheral or central vestibular dysfunction. The causes include inner ear problems, such as benign paroxysmal positional vertigo (BPPV), vestibular neuritis, Meniere's disease, labyrinthitis, and neurological diseases

Highlights

- Machine learning may predict vascular vertigo prior to hospital admission.
- Logistic regression model achieves the highest accuracy by 86%.
- Main discriminative features were albumin, age, headache, hypertension, and diabetes.
- Machine learning may reduce costs and provide timely intervention in dizziness.

such as vertebralbasilar ischemia, stroke, demyelinating disorders and neurodegenerative diseases.

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In clinical practice, the differential diagnosis of these symptoms presents a medical challenge (7). Definitive diagnosis necessitates a comprehensive assessment of medical history and physical examination. Additional diagnostic tests are often initiated due to the diversity of etiologies. These include audiological testing, videonystagmography (VNG), imaging studies such as brain magnetic resonance imaging (MRI) and doppler ultrasound of neck vessels. Actually, a great majority of the patients with dizziness have benign conditions and the diagnosis is straightforward when they meet the relevant specialist. Prior research showed that in 50% of patients with dizziness, the time to 'reach a diagnosis' was 5 months or longer, and 75% of these patients underwent MRI, which is a very expensive test(8). Considering the high prevalence of these complaints, it can easily be seen that there is a serious economic burden on the health systems and loss of labor force(9) (10).

On the other hand, some patients require neuroimaging without delay, especially to recognize some 'neurological emergencies'. These are patients with stroke, vertebrobasilar transient ischemic attack, intracranial hemorrhage and severe cerebral perfusion disorders. There is a time window of 4.5 hours in which acute treatment of vascular neurological pathologies is possible (11). Therefore, early diagnosis is very important for this patient group. Also, the disease may progress and the patient's neurological status may worsen. In clinical practice, it is not unusual that people with posterior circulation strokes meet the neurologists after otolaryngologists' visit, and sometimes after several tests.

Artificial intelligence is becoming very popular for solving many problems, especially in health and medicine. Many studies have been conducted using machine learning methods in a wide spectrum of medical conditions, including cancer, stroke, even in rare neurogenetic syndromes like neurofibromatosis etc. (12), (13), (14),(15), (16). Recently, state-of-the-art studies incorporating artificial intelligence in the field of dizziness have also been published. Kabade et al. stated that machine learning models can process patient history, examination findings, and test results to predict vertigo etiology (17). Anh et al. proposed a machine learning-based approach to classify peripheral vestibular (PV) and non-PV diseases using equilibrium function test data (18). Tang et al. proposed a machine learning model using clinical and laboratory data to effectively distinguish benign paroxysmal positional vertigo from non-benign paroxysmal positional vertigo and for further classification. The model achieved high diagnostic performance, with sensitivity up to 100% and area under the curve values above 0.93, demonstrating a high potential of machine learning algorithms in this particular field (19).

Main aim of this project is 1) to select the patients with dizziness that need to be managed by neurologists or emergency physicians rapidly by using machine learning algorithms, 2) to detect the clinical and biochemical features that facilitate the identification of vascular vertigo patients by machine learning methods. Early recognition and triage of these patients by an artificial intelligence- based tool may help prevent unnecessary medical visits and tests.

METHODS

Data Collection

A total of 470 dizziness patients were included in this study who were admitted to TOBB ETÜ hospital between May 2023 and May 2024. The records of these patients were obtained retrospectively from the database of neurology department of the TOBB ETÜ hospital. We created a dataset including the following information of the patients: age, sex, accompanying symptoms (imbalance, headache, double vision, tinnitus, paresthesia), fluctuations in dizziness or episodic nature, comorbidities (hypertension and diabetes), the definitive diagnosis, biochemical data including serum albumin, ferritin, transferrin, uric acid, triglyceride,

low density lipoprotein, high density lipoprotein, total cholesterol, vitamin B12, vitamin D, blood urea nitrogen, and creatinine. The experts (ATS, SU, EE) made a definitive diagnosis of each patient after reviewing all the diagnostic workup. The patients were grouped into six different categories: peripheral, vascular, migraine, other central vertigo, psychogenic, and nutritional. Hence, the dataset (n=470) was formed with the abovementioned 21 attributes of the participants as well as classes and was anonymized appropriately. The properties of the dataset are summarized in Table 1. Our goal in this study is to predict vascular cases among the others since they need to be managed promptly. For this reason, we assign a class label of 1 to cases involving vascular conditions; otherwise, we assign a class label of 0. The state-of-the-art machine learning methods are employed to predict patients suffering dizziness from vascular reasons on created dataset. This study was approved by the Ethics Committee of TOBB ETÜ (21.02.2024/BAEK02).

Machine Learning Methods

This study employs a total of six different machine learning techniques: decision tree, logistic regression, support vector machines, k-nearest neighbor, multilayer perceptron, and ensemble learning methods.

Decision trees (DTs) in machine learning serve as a data analysis technique for uncovering patterns within datasets (20). The structure of a decision tree comprises nodes and branches, with each node representing a feature and each branch denoting a value of that feature. The data is split into smaller groups, and predictions are made for each subgroup. The learning process involves routing instances through the tree branches based on feature values and making decisions at each node. Decision trees are widely used in both classification and regression tasks, and model parameters significantly impact performance.

Logistic regression (LR) is a supervised machine learning algorithm used for binary classification tasks, where it predicts the probability of an outcome, event, or observation occurring (21). It uses sigmoid function to map values to a probability between 0 and 1. To classify samples into two classes, the probability produced by sigmoid function is used.

Support Vector Machine (SVM) is a robust machine learning algorithm often employed for classification and regression tasks (22). Its primary objective is to classify data points by determining the optimal hyperplane that separates two classes. Support vectors are crucial points that maximize the margin between the classes. SVMs are highly effective, even in high-dimensional spaces, by leveraging kernel functions and performing well in classification and regression problems. In this study, we used linear kernel.

K-nearest neighbor (KNN) is a non-parametric, lazy learning classification technique (23). It bypasses the need for a dedicated training phase, instead storing the entire training dataset for use during classification. When classifying a new data point, the KNN algorithm identifies the k closest samples from the training set and assigns the new data point to the class based on majority voting. In this study, k was set to 1 and Euclidean distance was used.

The multilayer perceptron (MLP), a type of feed-forward artificial neural network, consists of three main layers: an input layer, one or more hidden layers, and an output layer (24). The input layer contains a number of neurons equal to the number of features in the dataset, while the output layer includes a single neuron that provides the MLP's output (25). MLP models data by employing activation functions, with commonly used ones including the logistic sigmoid, rectified linear unit (ReLU), and hyperbolic tangent (tanh). In this study, we utilized a basic MLP model with three hidden layers and ReLU activation function was used.

Ensemble techniques merge the predictions coming from machine learning methods to increase overall accuracy (26). Some widely used ensemble techniques are bagging, boosting, and stacking. In this study, we performed bagging and boosting methods.

Experimental Setup

The experiments were carried out on a computer equipped with a 2.6 GHz Intel Core i7 processor and 16 GB of RAM, running the Ubuntu 18.04.03 LTS operating system. To implement the classifiers, we utilized the Scikit-learn library, an open-source toolkit designed for machine learning in the Python language.

The performance of the machine learning models is evaluated based on precision, recall, F1-score, and accuracy metrics. Precision is the ratio of correctly predicted vascular positive cases to the total number of cases predicted as vascular positive. Recall is defined as the proportion of actual vascular positive cases that were correctly identified by the machine learning model. F1-score is the harmonic mean of precision and recall. The accuracy is the overall percentage of correct predictions, considering both correctly predicted vascular positive cases and correctly identified negative cases. It indicates the general effectiveness of the model in distinguishing between vascular positive and negative cases. We also give confusion matrices of the machine learning methods to evaluate comprehensively. Confusion matrices display the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). TP represents the number of correctly identified vascular positive cases, and FP denotes the number of incorrectly predicted vascular negative cases. TN refers to the correctly predicted vascular negative cases, while false negative FN indicates the number of incorrect predictions in the vascular positive class.

RESULTS

The mean age of the patients was 52.4 ± 17.8 (mean \pm standard deviation). Female/male ratio was 269/201. The number of patients in each class can be seen in Table 1 and a detailed analysis of clinical characteristics and laboratory values of patients are given in Table 2.

Table 3 presents importance scores calculated by ANOVA. ANOVA analysis evaluates whether the variance between the means of the attribute values of different groups is statistically significant compared to the total variance according to the F1-score. Higher F1-score presents that there is a significant difference between group means.

Figure 1 presents the confusion matrices of the DT, LR, SVM, KNN, MLP, and ensemble methods. The 'vascular-' includes peripheral, migraine, central vertigo, psychogenic, and nutritional cases. The results of the DT

methods reveal that 44 *vascular* samples (%50) are correctly classified while the remaining 44 *vascular* samples are incorrectly classified. In the 'vascular-' cases, 346 samples (%91) are classified correctly while 36 cases are classified incorrectly. The precision, recall, and F1-scores of the DT are 0.5, 0.55, and 0.52, respectively. The results of the LR method are the same with the DT for the *vascular cases* and more accurate results for the "vascular-" case. The precision, recall, and F1-scores of the LR are 0.5, 0.66, and 0.57, respectively. When we evaluate the results of the SVM method we see that it correctly identified 40 *vascular cases* (%45) while incorrectly labeling 48 positive cases as vascular negative. On the other hand, it accurately classified 362 negative cases (%95) but missed 20 actual vascular negative cases. The precision, recall, and F1-scores of the SVM are 0.45, 0.66, and 0.54, respectively. With the KNN method, 28 *vascular samples* (%32) are classified correctly and remaining 60 samples are classified incorrectly. On the other hand, it accurately classified 367 'vascular-' cases (%96) missing only 15 actual vascular negative samples. The precision, recall, and F1-scores of the KNN are 0.31, 0.65, and 0.42, respectively. With the MLP method, 46 *vascular samples* (%52) are classified correctly, while the remaining 42 samples are misclassified. On the other hand, while 338 'vascular-' samples (%88) are classified correctly, the remaining 44 samples are classified incorrectly. The precision, recall, and F1-scores of the MLP are 0.52, 0.51, and 0.52, respectively. Bagging method achieved the best results in the ensemble learning technique. With the ensemble method, 34 *vascular samples* (%39) are correctly classified, and 54 samples are misclassified. In the 'vascular-' group, 355 samples (%93) are classified correctly, and 27 samples are classified incorrectly.

Figure 2 presents accuracy results of the machine learning methods. Accuracy results range from 81.7% to 86% and the best result is achieved with the LR method. The DT, SVM, KNN, MLP, and Ensemble methods reached the accuracies of 83%, 85.5%, 84%, 81.7%, and 82.8%, respectively.

DISCUSSION

Differentiating potentially severe causes of dizziness from benign etiologies is a long-standing medical challenge. This paper presents a machine learning method to aid early diagnosis of vascular causes of dizziness. Detecting "vascular vertigo" with such computerized, fast and accurate techniques will enable urgent patients to consult a neurologist or admit emergency department without delay, ensure a definitive diagnosis at the time of first presentation. Thus, necessary therapeutic interventions can be initiated quickly.

Proposed method utilizes main clinical information (features defining dizziness, accompanying symptoms, some demographics, comorbidities)

Table 1. Group name and description of the kind of dizziness

Group name of dizziness	Description of the group	The number of patients	Class label
Peripheral	Benign positional paroxysmal vertigo, endolymphatic hydrops, Meniere's disease, vestibular neuritis	176	0
Vascular	Stroke, transient ischemic attack, hypertensive crisis, vertebrobasilar insufficiency, orthostatic hypotension	88	1
Migraine	Vestibular migraine	36	0
Other central vertigo	Neurodegenerative and demyelinating diseases	48	0
Psychogenic	Anxiety disorders, depression and somatoform disorders	71	0
Nutritional	Anemia with iron deficiency, vitamin B12 and vitamin D deficiencies	51	0

Table 2. Descriptive analysis of patients

	Groups of patients with dizziness					
	Peripheral	Vascular	Psychogenic	Vitamin Deficiency	Central	Migraine
Gender	Female 90 (19.1%) Male 86 (18.3%)	Female 43 (9.1%) Male 45 (9.6%)	Female 47 (10%) Male 24 (5.1%)	Female 29 (6.2%) Male 22 (4.7%)	Female 30 (6.4%) Male 18 (3.8%)	Female 29 (6.2%) Male 7 (1.5%)
Age (Mean):	50.59	71.93	44.26	40.41	58.25	39.28
Laboratory Values						
Serum Albumin (Mean):	4.521	4.265	4.45	4.983	4.258	4.483
Ferritin (Mean):	116.52	117.65	76.9	91.407	99.877	56.034
Transferrin (Mean):	29.433	26	28.33	20.75	21.143	36.2
Uric Acid (Mean):	5.314	5.625	5.392	4.657	5.525	4.773
Triglyceride (Mean):	162.808	165.35	136.536	113.25	157.556	98.261
Low Density Lipoprotein (Mean):	129.085	122.732	123.616	121	127.867	117.7
High Density Lipoprotein (Mean):	51.37	52.125	52.212	52.333	53.852	55.705
Total Cholesterol (Mean):	197.799	206.326	189.322	184.539	207.938	193.821
Blood Urea Nitrogen (Mean):	14.144	17.419	12.537	12.783	19.021	11.781
Vitamin B12 (Mean):	446.783	458.399	595.675	356.074	482.069	464.715
Vitamin D (Mean):	25.528	25.893	30.724	17.533	39.004	31.602
Clinical findings						
Complaints:						
Headache	Yes 55 (31.25%) No 121 (68.75%)	Yes 20 (22.73%) No 68 (77.27%)	Yes 30 (42.25%) No 41 (57.75%)	Yes 22 (43.14%) No 29 (56.86%)	Yes 13 (27.08%) No 35 (72.92%)	Yes 33 (91.67%) No 3 (8.33%)
Tinnitus	Yes 57 (32.39%) No 119 (67.61%)	Yes 14 (15.91%) No 74 (84.09%)	Yes 15 (21.13%) No 56 (78.87%)	Yes 15 (29.41%) No 36 (70.59%)	Yes 10 (20.83%) No 38 (79.17%)	Yes 11 (30.56%) No 25 (69.44%)
Paraesthesia	Yes 38 (21.59%) No 138 (78.41%)	Yes 8 (9.09%) No 80 (90.91%)	Yes 20 (28.17%) No 51 (71.83%)	Yes 11 (21.57%) No 40 (78.43%)	Yes 9 (18.75%) No 39 (81.25%)	Yes 7 (19.44%) No 29 (80.56%)
Imbalance /Walking Disorder	Yes 89 (50.56%) No 87 (49.44%)	Yes 56 (63.64%) No 32 (36.36%)	Yes 26 (36.62%) No 45 (63.38%)	Yes 24 (47.06%) No 27 (52.94%)	Yes 30 (62.5%) No 18 (37.5%)	Yes 15 (41.67%) No 21 (58.33%)
Diplopia	Yes 6 (3.4%) No 170(96.6%)	Yes 3 (3.41%) No 85 (96.59%)	Yes 1 (1.41%) No 70 (98.59%)	Yes 1 (1.96%) No 50 (98.04%)	Yes 3 (6.25%) No 45 (93.75%)	Yes 1 (2.78%) No 35 (97.22%)
Comorbidities: Hypertension	Yes 50 (28.4%) No 126 (71.6%)	Yes 47 (53.41%) No 41 (46.59%)	Yes 14 (19.72%) No 57 (80.28%)	Yes 6 (11.76%) No 45 (88.24%)	Yes 27 (56.25%) No 21 (43.75%)	Yes 5 (13.89%) No 31 (86.11%)
Diabetes Mellitus	Yes 24 (13.64%) No 139 (78.97%) Insulin Resistance 13 (7.39%)	Yes 21 (23.86%) No 58 (65.91%) Insulin Resistance 9 (10.23%)	Yes 5 (7.04%) No 61 (85.92%) Insulin Resistance 5 (7.04%)	Yes 3 (5.88%) No 45 (88.24%) Insulin Resistance 3 (5.88%)	Yes 13 (27.08%) No 31 (64.58%) Insulin Resistance 4 (8.34%)	Yes 2 (5.56%) No 34 (94.44%) Insulin Resistance 0 (0%)
Characteristics of Vertigo:						
Recurrent	167 (94.89%)	86 (97.73%)	65 (91.55%)	49 (96.08%)	46(95.83%)	34 (94.44%)
First-time	9 (5.11%)	2 (2.27%)	6 (8.45%)	2 (3.92%)	2 (% 4.17)	2 (%5.56)

and some already-known biochemical data of the patient as a pre-assessment tool.

As presented in Table 1, the top five features exhibiting the highest discriminative power in our study were serum albumin, age, presence of headache, presence of hypertension and diabetes. Age, hypertension, hyperlipidemia (LDL in our study) and diabetes are risk factors for vascular events. Albumin is the major protein constituent of plasma. It is also an endogenous circulating antioxidant (27). Advanced age, malnutrition and some metabolic diseases may cause reduced albumin levels. Clinically, it is unlikely to relate albumin directly to dizziness. Hypoalbuminemia may rather be an epiphenomenon in neurodegenerative diseases and age-related health problems which also cause dizziness (28). Features that do not appear clinically important for diagnosis may be meaningful and

valuable in the implicit patterns of big data. On the other hand, diplopia is mostly a serious symptom that alerts the clinician. Among the features we included, it appeared to be the least effective in classifying dizziness by machine learning. The reasons for this may include that the symptom might not be defined correctly by the patients. It becomes clear after a detailed medical history taking and full neurological examination whether the patient is suffering double vision, oscillatory vision, monocular diplopia or binocular diplopia. This emphasizes the core necessity of human expertise in clinical decision making.

Clinical tests were not included in our dataset. High-dimensional data improves the classification accuracy of machine learning algorithms and several studies have been performed including the physical examination findings, clinical and laboratory tests, and radiological data (29) (30) (31)

Table 3. Feature importance scores using ANOVA algorithm

Feature Name	F1-Score
Serum albumin	98.48
Age	98.48
Headache	26.92
Hypertension	22.95
Diabetes	8.71
Gender	5.09
Imbalance	4.87
Low Density Lipoprotein	3.89
Tinnitus	2.84
Paresthesia	2.59
Transferrin	1.99
Blood Urea Nitrogen	1.89
Triglyceride	1.56
Vitamin D	1.47
Uric acid	1.09
High Density Lipoprotein	0.58
Ferritin	0.49
Recurrent type	0.45
Total cholesterol	0.42
Vitamin B12	0.29
Diplopia	0.25

(32) (33) (34). Some of these studies included only the peripheral causes, some only a specific etiology, and most included the diagnostic clinical tests already performed by the clinician. Our aim was a fast and accurate tool for triage of dizzy patients. Here, we provide an assistive model for directing the patients to proper medical branches and determining potentially serious cases that need emergency care. Including clinical tests, examination findings of the physician and specific laboratory tests would likely increase the accuracy.

The performance of machine learning methods in health applications has been variable. Seven et al. evaluated machine learning methods for predicting survival in hepatocellular carcinoma patients using clinical, pathological, and laboratory data from 393 cases. The models showed strong performance, with up to 91% recall for early-stage survival and 92% accuracy for advanced-stage predictions (12). Esen et al. presented a machine learning-based approach for predicting gallstone disease (GD) using bioimpedance and laboratory data, addressing limitations of traditional imaging methods. A dataset of 319 participants (161 with GD and 158 healthy) with 38 features was used. Analysis identified vitamin D, CRP levels, total body water, and lean mass as key predictors. Gradient boosting achieved the highest prediction accuracy at 85.42%, highlighting the potential of this method as a cost-effective and non-invasive alternative for early GD diagnosis (35). Kos et al. evaluated the use of machine learning models to predict overall and time-specific survival in patients with non-metastatic colorectal cancer (CRC). Data from 498 patients with over 10 years of follow-up were analyzed. Five machine learning algorithms were tested, with the decision tree model performing best for 1-year survival (AUC 0.89), the ensemble model excelling for 2- to 5-year predictions, and the support vector

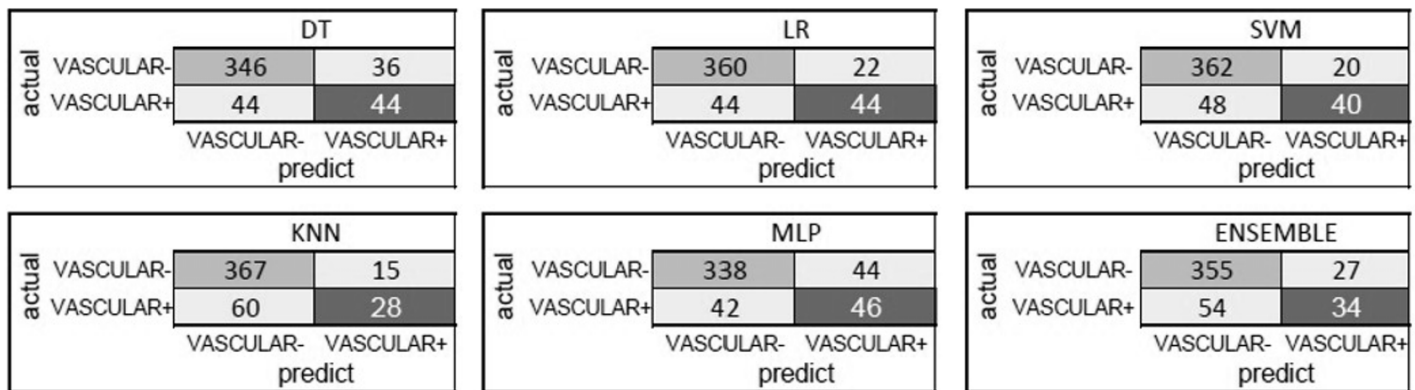


Figure 1. Confusion matrices of the machine learning methods

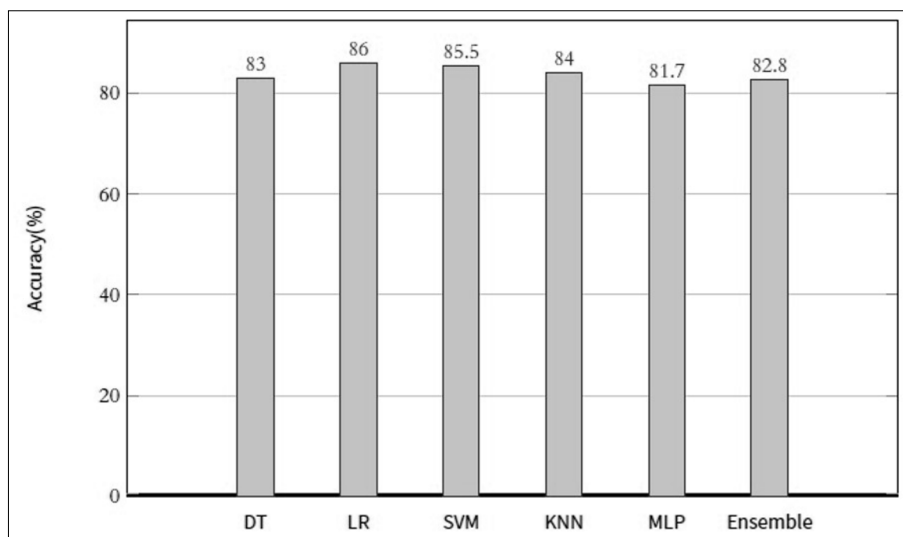


Figure 2. Accuracy results of the machine learning methods

machine model performing best for 10-year survival (AUC 0.84). All models showed around 70% or higher accuracy across cancer stages, demonstrating the potential of machine learning in predicting both short- and long-term CRC outcomes (13). Sharafi et al. investigated clinical differences between sporadic and familial Neurofibromatosis type 1 and evaluated machine learning models to predict sporadic cases based on symptoms. Analyzing 241 patients, key clinical features varied significantly between groups. Among several algorithms tested, XGBoost showed the highest prediction accuracy at 62.86%, suggesting moderate potential for aiding diagnosis alongside traditional methods (14).

One of the highest accuracies have been reported by Wang et al. that proposed a machine learning tool to differentiate vestibular migraine and Meniere's disease (29). They used patient history, video-nystagmography, and audiovestibular test data. Trained on data from 274 patients, 160 of whom were diagnosed with vestibular migraine, the models achieved high accuracy across three clinical settings, with AdaBoost and Random Forest performing the best. They limited the study population by two types of recurrent spontaneous vertigo. The more homogenous the dataset, the better the model learns and the higher the accuracies. The differential diagnosis of dizziness includes a larger spectrum of diseases; therefore, our dataset was inevitably heterogenous. Lu et al. proposed a deep learning method for diagnosing benign paroxysmal positional vertigo (30). They collected eye movement video data belonging to 518 patients. Their method achieved an accuracy of 81.7%. Kim et al. proposed a machine learning based model to diagnose acute central dizziness using simple clinical data (33). They analyzed 5048 patients and they achieved an AUC score of 0.73, a sensitivity of 94.4%, and a specificity of 31.9%. The main drawback of their method is its lower specificity. Additionally, they divided the dataset into training and testing sets without performing cross-validation. If cross-validation had been performed, the performance of the machine learning method might have decreased.

Our main focus was early differentiation of vascular vertigo patients. Thus, we analyzed the dataset in a binary fashion as vascular vs the others. The accuracy values of the other individual groups were low. This may result from the small size of some of the subsets since the most effective factor in machine learning is the size of the dataset. Another reason may be the missing values in clinical records.

In the proposed study, the best performing machine learning method was logistic regression model. Its accuracy was 0.86 in classifying vascular vs nonvascular dizziness cases correctly. It can be seen that there are still vascular cases that are missed by this method. Each registry to the system improves the model. We had 88 vascular cases. The tool is expected to perform better with increasing group size. Another significant clinical reason for the missed cases may stem from the inherent heterogeneity within the vascular vertigo group itself. This category encompasses quite different etiologies, each with distinct pathophysiological mechanisms. Notably, it includes not only stroke-related vertigo—typically characterized by acute-onset, persistent symptoms generally with clear neurological deficits—but also cases of severe hypotension, presyncope, and syncope, where transient cerebral hypoperfusion leads to episodic dizziness. While stroke-induced vertigo often presents with focal ischemic signs (e.g., nystagmus, ataxia, or cranial nerve involvement), hypoperfusion-related dizziness tends to manifest as brief, recurrent episodes triggered by orthostatic changes or cardiac dysfunction. The classification of these diverse conditions under a single “vascular vertigo” label, though clinically justifiable due to their shared vascular etiology, introduces diagnostic complexity. Stroke or transient ischemic attack-related vertigo requires urgent neuroimaging and intervention, whereas hypotension-related dizziness may demand

prompt cardiological or autonomic evaluation. This variability in underlying pathology and related clinical features likely contributed to the model's reduced accuracy in this subgroup.

As can be seen, the main limitation of our study is the wide spectrum of the causes of dizziness. This results in relatively small numbers of patients in each class as discussed. Another limitation may be the demographic profile of the patients that admit our hospital. TOBB ETÜ hospital is a private foundation university hospital, so the demographic features of our sample may not adequately represent the study population.

In conclusion, we have demonstrated that machine learning algorithms can effectively recognize vascular vertigo patients using some clinical and biochemical data. Our model can be beneficial for the ambulance personnel, emergency physicians, practitioners and also for the specialists facing atypical and difficult cases. Integration of artificial intelligence in health service can improve the quality of patient care and reduce health expenditures.

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Data availability: The dataset used for this study contains patient health data and is not publicly available for privacy reasons. A deidentified version of dataset is available on reasonable request from the corresponding author.

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