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Review

Machine Learning Techniques for Acute Vertigo/Dizziness: A Review

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Abstract: Vertigo is a sensation of movement that results from disorders of the inner ear balance organs and their central connections, with aetiologies that are often benign and sometimes serious. An individual who develops vertigo can be effectively treated only after a correct diagnosis of the underlying vestibular disorder is reached. Recent advances in artificial intelligence promise novel strategies for the diagnosis and treatment of patients with this common symptom. Human analysts may experience difficulties manually extracting patterns from large clinical datasets. Machine learning (ML) techniques can be used to visualize, understand, and classify clinical data to create a computerized, faster, and more accurate evaluation of vertiginous disorders. Practitioners can also use them as a teaching tool to gain knowledge and valuable insights from medical data. Here, we provide a review of the papers from 1999 to 2021 using various feature extraction and machine learning techniques to diagnose vertigo disorders. This paper aims to provide a better understanding of the work done thus far and to provide future directions for research into the use of ML in vertigo diagnosis.

Keywords: Artificial Intelligence; Vertigo; Dizziness; Machine learning; Feature extraction.

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1. Introduction

Dizziness is a broad term that encompasses various symptoms, including unsteadiness, vertigo, and light-headedness or presyncope, as shown in Figure 1. Vertigo is an illusion of rotation, tilt, or any other movement of oneself (subjective vertigo) or one's surroundings (objective vertigo) in any plane. It can be classified by aetiology into "peripheral" or "central," depending on the location of the dysfunction of the vestibular pathway. The vertigo that is caused by problems affecting the inner ear balance-organs or vestibular end-organs; the vestibular nerve or Scarpa's ganglion is classified as peripheral [1]. In contrast, vertigo that arises from disorders affecting the balance centers of the central nervous system (in the brain stem, cerebellum, or vestibular cortex) is classified as central [2]. Figure 1 illustrates common causes of different subtypes of dizziness. The most common causes of peripheral vertigo are Benign Paroxysmal Positional Vertigo (BPPV), Meniere's Disease (MD), and Vestibular Neuritis (VNE). The most encountered causes of central vertigo include vestibular migraine and posterior circulation stroke [3-6]. Since this classification is only applicable after a final diagnosis has been reached, a syndromic approach to vertigo has been adopted in a clinical setting. Acute Vestibular Syndrome

(AVS) refers to a single attack of severe vertigo lasting >24 hours, nausea and vomiting with postural instability, and is usually accompanied by spontaneous nystagmus [7]. Peripheral causes of AVS include Vestibular Neuritis (VN), an innocuous viral inflammation of the vestibular nerve [8]. A posterior circulation stroke may cause central AVS, a life-threatening illness requiring urgent imaging and immediate treatment with oral antiplatelet and sometimes endovascular therapies [9]. Episodic Spontaneous Vertigo (ESV) refers to recurring attacks of spontaneous vertigo lasting >1 minute, not triggered by changes in head movement [10]. One of the most common causes of ESV is Vestibular Migraine (VM), causing spinning/swaying vertigo with a history of current or past migraines, and Meniere's Disease (MD), characterized by violent spinning vertigo, hearing loss, aural fullness, and tinnitus due to fluid build-up in the inner ear [11, 12]. Episodic Positional Vertigo (EPV) refers to vertigo recurring due to changes in head position and is characterized by brief spells of spinning vertigo. EPV is most often due to Benign Paroxysmal Positional Vertigo (BPPV) caused by calcium carbonate particles dislodged into the semicircular canals or in some cases caused by Vestibular Migraine or Central Positional Vertigo [13, 14].

Vertigo is a widespread and distressing symptom that may occur at any age. Dizziness (including vertigo) affects about 15% to over 20% of adults yearly in extensive population-based studies. Vestibular vertigo accounts for about a quarter of dizziness complaints and has a 12-month prevalence of 5% and an annual incidence of 1.4% [15]. In most affected individuals, vertigo results in a medical consultation, interruption of daily activities, or sick leave [16]. Prevalence and incidences increase with age and are reported much higher in women than in men [15]. In one study [17], the prevalence of vertigo and dizziness in people aged more than 60 years was found to be 30%. The presence of dizziness in the elderly can be a strong predictor of falls, leading to accidental death [18].

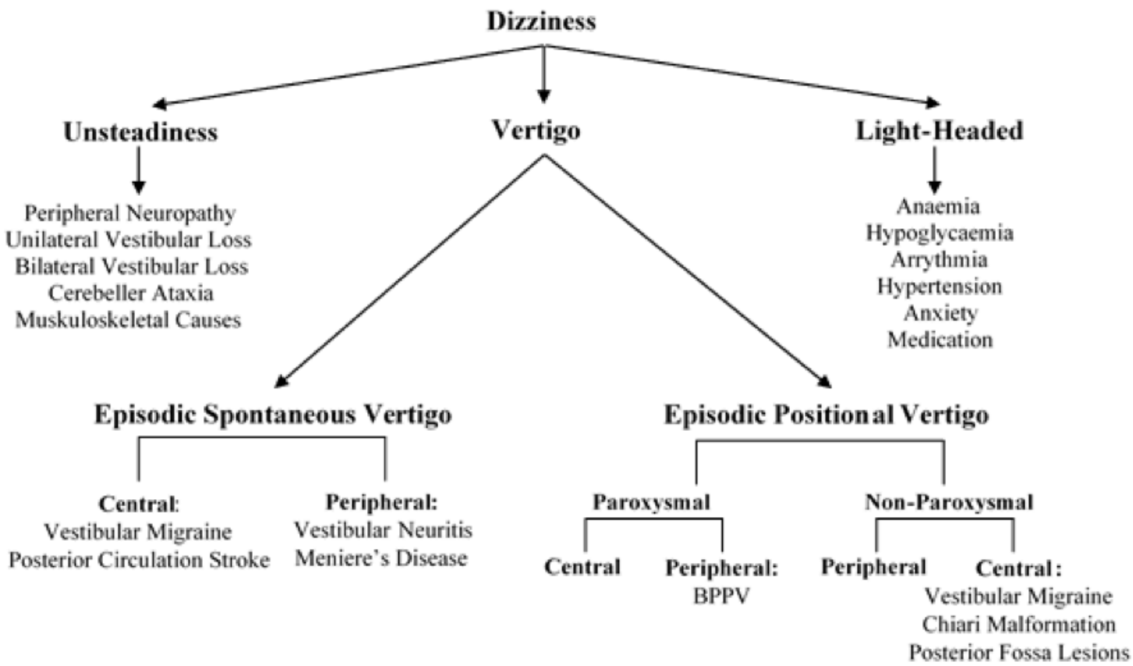

Figure 1: A flowchart depicting the differential diagnosis of dizziness

Vertigo, being such a common symptom in the general population, merits an organized approach to early and accurate diagnosis of the underlying cause by healthcare practitioners. Often a patient is misdiagnosed or referred to the incorrect specialist, prolonging the symptoms and increasing associated morbidities. Such misdiagnosis is costly to the patient, the healthcare system, and the economy, inefficient, and potentially harmful. Neuhauser HK [15] suggests that BPPV and Vestibular migraine (VM) are underdiagnosed while MD is usually over-diagnosed. Dizziness and vertigo account for about 4% of presenting symptoms in the emergency department (ED)[19]. Stroke accounts for 4-15% of patients, and around 10% are missed at first contact, with a substantial increase in morbidity and mortality [20]. Ahmadi SA et al. [21] propose that machine-learning methods have the potential to perform better than clinical scores (e.g., HINTS (head impulse, nystagmus type, test of skew); ABCD2 (age, blood pressure, clinical features, duration of symptoms, diabetes) in stroke detection.

Machine Learning (ML) is widely being used in disease diagnosis where faster and more reliable results are required. It is also being used to analyse the importance of clinical parameters and their combinations for prognosis, e.g., prediction of disease progression, for the extraction of medical knowledge for outcomes research, therapy planning and support, and overall patient management. Many machine learning techniques have been used for the differential diagnosis of vertigo over the last few decades. These models process the patients' data, find the correlations and associations of presenting symptoms, familiar antecedents, habits, background medical history of making predictions. The machine learning models most commonly used in vertigo diagnosis include Decision trees [22-26], Support Vector Machines (SVM) [22, 26-34] and k-Nearest neighbours (KNN) [20, 23, 26-28, 31, 35, 36] with deep learning techniques [24, 25, 37]. Some researchers have also used novel ML algorithms and Ensemble Learning to improve diagnostic accuracy [29, 34, 38, 39].

This paper aims to provide a comprehensive analysis of the application of artificial intelligence in the diagnosis of vertigo. The rest of the paper is arranged as follows: Section 2 discusses different datasets and features used to train models. Section 3 explains the machine learning algorithms utilized for vertigo type classification, covering their advantages and disadvantages. Section 4 provides a review of different ML techniques used in literature followed by a discussion in Section 5 with possible future directions for researchers.

2. Data Collection and Analysis for Machine Learning in a Specialist Vertigo Clinic

To train ML models, a large amount of data is required. The first step to creating an ML model is data collection, as shown in Figure 2, which includes data acquisition and data labelling. This may involve gathering history, examination, and vestibular test data in a large number of patients who have been classified by diagnosis). Post collection, the data usually needs to be cleaned, transformed, and formatted before feeding into a machine learning model (for example, nystagmus data may need removal of blink artifacts). Depending on the data and the model of choice, feature engineering and feature selection can make the training computationally tractable and help create a more robust and accurate model.

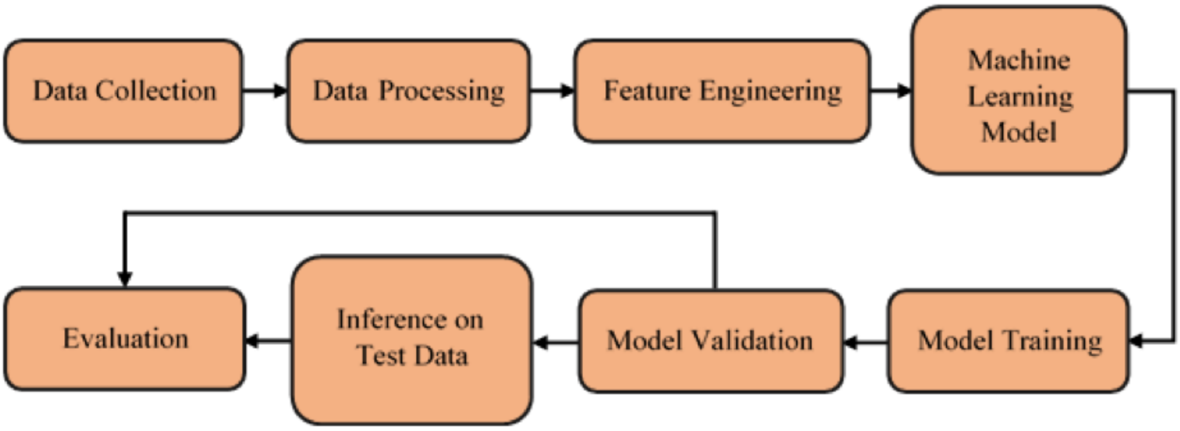

Figure 2: Machine Learning workflow

In a specialty clinic, the diagnostic process of the non-specific symptom of dizziness involves first eliciting information on the patient's background medical history (comorbidities) and then clarifying presenting symptoms (whether the vertigo is spontaneous or positional, its duration and associated phenomena). Next, a clinical examination is performed; important components are a general inspection for head tilt, obvious cranial nerve palsies and Horner's Syndrome, assessment for spontaneous, gaze-evoked, and positional nystagmus, head impulse testing, tests of standing balance such as the Matted Romberg, Unterberger tests and tandem walking, screening neurological tests for limb weakness and ataxia and postural blood pressure testing. In many instances an expert clinician will arrive upon a diagnosis with the history and examination; in others, audio vestibular tests, which interrogate the cochlear and vestibular end-organ function are sought. The most conducted tests are audiometry to assess cochlear function, caloric testing, rotational chair testing, video head impulse tests to assess horizontal semi-circular canal function and vestibular evoked myogenic potentials to test otolith function. These tests require a history and physical examination to be meaningful. Posturography and gait analysis are now seldom used in the differential diagnosis of vertigo but can help identify vestibular disorders as a cause of imbalance, estimate the risk of falls, monitor the disorder's progression, and track treatment effects [40]. Screening laboratory tests such as a complete blood count, electrolytes, thyroid function tests, vitamin B1 and B12 levels and iron studies, seeking nutritional and metabolic causes of dizziness and imaging studies (MRI Brain, CT angiography, CT Petrous temporal bones with canal plane reconstructions) seeking a structural cause for dizziness are often undertaken.

ONE [41] was an early expert system developed to aid the diagnosis of vertigo. It implemented a database of vertiginous patients for research purposes and used this database in several research studies [42, 43]. The data included was collected through a questionnaire related to presenting symptoms, comorbidities, and results of vestibular, audiology, and imaging tests amounting to 170 variables. DizzyReg [24] is a modern clinical registry containing information on history, examination, test results, diagnosis, treatment, and outcome of patients with vertigo and dizziness. It contains anamnestic, sociodemographic, diagnostic, and therapeutic information of patients presenting with vertigo, including duration and type, neurological examination findings, audio vestibular test results, and the video head impulse test amounting to over 300 variables. The data was collected through the perusal of medical reports and questionnaires and used for intelligent diagnosis of vestibular disorders in [24]. The Dizziness Handicap Inventory (DHI) [34] is a validated questionnaire of twenty questions for quantitative evaluation of the degrees of handicap in the daily lives of patients with vestibular disorders. Data collected using

DHI has been used for differential diagnosis of Posterior Canal - Benign Paroxysmal Positioning Vertigo (PC-BPPV) and Horizontal Canal - Benign Paroxysmal Positioning Vertigo (HC-BPPV) via machine learning techniques [34].

It is conceivable that a modern database created for diagnosis of vestibular disorders would consist of detailed history, physical examination and laboratory test data as well as expert diagnoses, treatments and their outcomes quantified by using validated questionnaires such as the Dizziness Handicap Inventory (DHI) or Vertigo Symptom Scale (VSS) [26, 44]. Once data are collected and pre-processed, a machine learning algorithm is chosen, and a model is trained on the data. A model to be used for diagnostic assistance should exhibit high sensitivity and high specificity.

3 Overview of Machine Learning Techniques

This section introduces various machine learning algorithms utilized in the existing research for classifying various vertigo types and covers their mathematical background with their advantages and disadvantages in Table 1.

Support Vector Machines: A Support Vector Machine (SVM) [45] is a supervised learning algorithm that constructs a hyperplane or set of hyperplanes separating data points from different categories in a multi-dimensional space. The algorithm has wide applications in various tasks such as classification, regression, and outliers' detection. After training the SVM model on a labeled dataset, the algorithm categorizes new data points into one of the categories depending upon their distance from the hyperplane. SVMs are also capable of classifying linearly inseparable data by using the kernel method where input vectors are non-linearly mapped to a multi-dimensional feature space. Kernel methods exploit mathematical techniques to achieve maximum stability and performance in terms of generalization and computation cost.

Naive-Bayes classifier: Naive Bayes [46] is a probabilistic classification algorithm based on the Bayes theorem with naïve and robust independence assumptions. It simplifies learning by assuming that features are independent of each other given a class. The algorithm performs extremely well in a supervised environment. This model does not require the use of any Bayesian models, instead it uses the maximum likelihood method for parametric estimation. The various types of naive bayes algorithm include Gaussian naive bayes for continuous data, multinomial naive bayes and Bernoulli naive bayes. The algorithm is suitable for large voluminous datasets and works extremely well for multi-label classification.

Decision trees classifier: A decision tree [47] is a classifier expressed as a recursive partition of the instance space. The decision tree forms a rooted tree. Each path from the root node of the decision tree to a leaf node can be regarded as a rule that leads to a particular class through different attribute tests (nodes). Each internal node splits the instance space into two or more sub-spaces based on a specific discrete function of the input attribute values. The class, for instance, is the class of the final leaf node. A good quantitative measure of the worth of an attribute is a statistical property called information gain that measures how well a given attribute separates the training examples according to their target classification. This measure is used to select among the candidate attributes at each step while growing the tree.

K-Nearest Neighbours: K-Nearest Neighbours (KNN) [48] is a non-parametric classification method that assigns a category to a data point depending upon the classes of its k-nearest neighbours. The nearest neighbours are determined by calculating a distance metric typically using euclidean distance, manhattan distance or hamming distance formula. KNN is a type of instance-based learning, or lazy learning, where the function is only locally approximated. For high-dimensional data (e.g., with the number of dimensions more than 10), dimension reduction is usually performed prior to applying the k-NN algorithm to avoid the effects of high- dimensionality. The local approximation feature reduces the training period and makes this algorithm robust.

Neural Networks: An artificial neural network (ANN) [49] is a mathematical model or computational model emulating a biological neural system. Each neuron is a node that is connected to other nodes via links that correspond to biological axon-synapse-dendrite connections. Each link has a weight, which determines the strength of one node's influence on another. Artificial Neural Networks are highly used machine learning models that can model highly non-linear patterns of data. Types of ANN include Self-organising map (Kohonen network), which is a type of artificial neural network (ANN) that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretized representation of the input space of the training samples, called a map, and is, therefore, a method to make dimensionality reduction; Convolutional Neural Networks (CNN) that have proven remarkably successful in processing visual and other two-dimensional data.

Genetic algorithms: Genetic Algorithms [50] are used to solve optimization and search problems by simulating the biological process of natural selection through steps such as selection, crossover, and mutation. Each generation consists of a population of individuals, and each individual represents a point in search space and a possible solution. Selection rules select the individuals from the population called parents from the given generation. Crossover rules combine two parents to form children for the next generation, and mutation rules apply random changes to the parents before forming children. After some generations, the "fittest" solution is selected. The whole algorithm can be summarised as follows:

i) Randomly initialize the population
ii) Determine fitness scores of the population
iii) Repeat until convergence:
   a) Select a set of parents from the population
   b) Crossover and generate a new population
   c) Perform mutation on the new population
   d) Calculate fitness scores for new population

Genetic algorithms can be used for feature selection, model hyper parameter tuning, and machine learning pipeline optimization concerning machine learning.

Table 1: Advantages and disadvantages of algorithms commonly used for vertigo classification

Algorithm	Advantages	Disadvantages
Decision Trees [51]	Requires less pre-processing, does not need normalization and scaling, no need of data imputation	Instability, complex calculations, high training time, resource expensive, does not work with continuous values
Support Vector Machines [52]	Efficient with distinctive classes, high dimensional data spaces, memory efficient, excellent for few data samples	Poor performance with large datasets, sensitive to noise and overlapping classes, underperforms when no. of features > no. of samples
K-Nearest Neighbor [53]	No training period, faster execution, supports dynamic data addition, needs only two parameters	Poor performance with large datasets, inefficient with high dimensional data, scaling, and normalization required, sensitive to noise, outliers, and missing values

Naïve Bayes [54]	Time inexpensive, supports multi-label classification, needs less training samples, best suited for categorical data	Less applicability in real-life scenarios due to feature independence, assigns zero probability to missing values
Genetic Algorithms [55]	Highly accurate, provides optimal results, robust and straightforward	Computation expensive, requires high parameter optimization
Neural Networks [56]	Automatic feature extraction, robust to data variations, scalable to large data volumes, adaptive to varying problems	Requires large training set, resource expensive, high computation time, complex to comprehend and optimize

4. Machine Learning Approaches used in the Differential Diagnosis of Vertigo

This section reviews the existing literature on machine learning approaches used for vertigo classification. We follow a feature-based approach to organize the literature. Subsection 4.1 examines the literary sources that implemented machine learning algorithms on dataset ONE. Subsection 4.2 elaborates on the works utilizing questionnaire-based features, while subsection 4.3 discusses the techniques using nystagmus features, and finally, subsection 4.4 reviews the literature that uses posturography and gait features for vertigo identification.

4.1 Machine Learning Applications on dataset ONE

ONE [41], an early expert system for vertigo, was developed as a diagnostic aid to assist teaching and implement a research database. The database of ONE consisted of patients' responses to 170 questions relating to symptoms and background medical history, and clinical test findings. A method based on pattern recognition was used in the reasoning process with attribute weights initially set by otoneurological experts. Machine learning techniques were applied to posturography and gait analysis, nystagmus data gathered in this dataset [22, 27-30, 57]. Lim EC et al. [35] used video data collected from videos of positional nystagmus induced by ten positional tests to identify the affected canal in BPPV patients. They used a convolutional neural network for classification using ten-fold cross validation arriving at an f-measure of 79.1%. Rasku J et al. [42] developed Galactica, a genetic algorithm approach to discover differential diagnostic rules to classify data into six dissimilar otoneurological diseases (BPV, Meniere's Disease, Sudden Hearing Loss, Vestibular Neuritis, Vestibular Schwannoma, Traumatic Vertigo) taken from ONE's database. Their proposed genetic algorithm developed IF-THEN rules from the questionnaire dataset, annotated as positive or negative. The authors used a sample size of 200 patients, setting 150 as the number of generations and keeping 0.95 and 0.01 as the probabilities of crossover and mutation, respectively. The accuracy of the rules was above 90% for all diseases except Meniere's disease, for which the accuracy level was 81%. Varpa K et al. [31] noted that combining machine-learned weights with expert knowledge gave the best classification results, classifying 82.5–84.7% of cases correctly within the first and second diagnostic suggestion.

Missing data limits the applicability of various machine learning algorithms. Data imputation is used to overcome this drawback where missing values in continuous data are replaced by the mean or median of the specific feature and replaced by the mode in categorical values. The results achieved by machine learning after imputation depend on the size of missing values, where accuracy decreases with the rise in the number of missing items. Laurikkala et al. [58] studied the usefulness of different imputation techniques such as means, regression, expectation-maximization, and random imputation to treat missing values in this dataset to allow for multivariate statistical analysis. They found that the discriminant functions obtained from imputed data were highly accurate for all the methods (93-96%). Their findings indicated that the missing data did not adversely affect disease classification. Miettinen et al. [59] employed Bayesian methods on ONE database to classify diseases accurately. Bayesian probabilistic models could also reveal dependence relations between attributes used for classification. Juhola et al. [23] compare KNN, discriminant analysis, k-means clustering, decision trees, Multi-Layer Perceptron (MLP) networks, and Kohonen networks on this data after data preprocessing with Principal Component Analysis (PCA). Linear discriminant analysis performed the best, followed by MLP networks.

Varpa, Kirsi et al. [31] compares attribute weighting methods with decision support system ONE and One-vs-All (OVA) KNN classifier to classify nine vertiginous diseases (see Table 2). The best total accuracy was achieved with the attribute weighted 5-nearest neighbor OVA method using the Scatter weights. They used a genetic algorithm-based approach for attribute weighting in ONE, class weighted KNN and OVA weighted KNN, which improved disease classification accuracy, median, and true positive rates of all the methods. They compared One-vs-All and One-vs-One methods in KNN and SVM and found that using multiple binary classifiers (one vs. one) improved the true positive rates of disease classes. Joutsijoki H et al. [60] used Half-Against-Half (HAH) architecture with SVM, KNN, and Naïve Bayes (NB) methods with HAH-SVM reaching similar accuracy as OVO-SVM. Juhola M et al. [61] tested the classification capability of neural networks on ONE database. Since the data had unbalanced distribution, MLP and Kohonen networks could detect the big classes with high specificity but failed to detect the smaller classes. Siermala M et al. [32] creates a set of neural networks for each disease class and artificial cases for smaller classes. It was found that this methodology could successfully deal with class imbalance, giving high classification accuracy even for smaller classes. Shilaskar, Swati et al. [33] dealt with a class imbalance on this dataset by synthetic oversampling of minority class and under-sampling of majority class and using modified PSO algorithm for feature selection and SVM for improving accuracy.

Table 2 summarizes the results for studies done on the dataset ONE, showing the mean accuracy (Acc), mean specificity (Spec), mean sensitivity (Sens), and mean F1-score for all target classes. VS-Vestibular Schwannoma; BPPV-benign paroxysmal positional vertigo; MD-Menière's disease; SD-Sudden deafness; TV-Traumatic vertigo; VNE-Vestibular Neuritis; VES-Vestibulopatia; BRV-Benign recurrent vertigo; CL-Central lesion; ANE-Acoustic Neuroma.

Table 2: Performance of machine learning algorithms on dataset ONE

Year	ML Algorithm	Target	Sample Size	Evaluation	Performance			
					Acc.	Sens.	Spec.	F1
2000 [58]	Discriminant Analysis + Regression Imputation	VS vs BPPV vs MD vs SD vs TV vs VNE	564	176 test cases	95	95	90	-
	k-nearest neighbor(k=5)	VS vs BPPV vs MD vs SD vs	815	10-fold CV	93.5	85.45	-	-
	Linear Discriminant Analysis				95.5	91.81	-	-

2008 [23]	K-means clustering (k=20)	TV vs VNE			92.9	84.83	-	-
	Decision Trees				89.4	71.45	-	-
	Multi-Layer Perceptron Network				95.0	90.46	-	-
	Kohonen Network				92.7	82.95	-	-
2008 [32]	Perceptron Neural Networks	ANE vs BPPV vs MD vs SD vs TV vs VNE vs BRV vs CL vs VES	815	815	95	85	83	-
2010 [59]	Naive Bayes	ANE vs BPPV vs MD vs SD vs TV vs VNE	815	10-fold CV	97	90	-	-
	Tree Augmented Naive Bayes				97	89	-	-
	General Bayesian Network				97	91	-	-
2011 [31]	k-nearest neighbor(k=5)	ANE vs BPPV vs MD vs SD vs TV vs VNE vs BRV vs CL vs VES	1030	10-fold CV	79.8	77.9	-	-
	One-vs-One Support Vector Machines-linear				77.4	82.4	-	-
	One-vs-One k-nearest neighbor (k=5)				82.4	88.2	-	-
	One-vs-All Support Vector Machines-rbf				79.4	78.6	-	-
	One-vs-All k-nearest neighbor (k=5)				78.8	77.7	-	-
2013 [60]	Half And Half Support Vector Machines-linear	ANE vs BPPV vs MD vs SD vs TV vs VNE vs BRV	1030	10-fold CV	76.9	-	-	-
	Half And Half k-nearest neighbor (k=9)				61.5	-	-	-
	Half And Half Naive Bayes				65.9	-	-	-

	Multinomial Logistic Regression				68.3	-	-	-
2014 [62]	Genetic Algorithm class weighted k-nearest neighbor(k=9)	ANE vs BPPV vs MD vs SD vs TV vs VNE vs BRV	951	10-fold CV	68.8	64.1	-	-
	Genetic Algorithm One-vs-All weighted k-nearest neighbor(k=3)				79.5	74.9	-	-
2016 [33]	Feed forward Neural Networks	ANE vs BPPV vs MD vs SD vs TV vs VNE	815	5-fold CV	84	84	97	84
	Grid based SVM				91	91	98	91
	Forward feature selection based SVM				90	90	98	90
	Genetic algorithm based SVM				92	92	98	92
	Modified PSO algorithm based SVM				94	94	99	94
2017 [63]	Weighted One-vs-all k-nearest neighbour(k=5)	ANE vs BPPV vs MD vs SD vs TV vs VNE vs BRV	1030	10-fold CV	79.7	75.2	-	-

4.2 Machine Learning Applications to Questionnaire-based Information and Multi-feature Datasets

Machine learning and statistical techniques applied to other questionnaires and multi-feature databases containing relevant information about the patients' history, clinical test findings, symptoms etc., have also been used for creating intelligent diagnostic systems [26, 35, 41, 43, 44]. Ahmadi SA et al. [21] compares machine learning approaches on multi-feature data set (including a standardized assessment of symptom features, cardiovascular risk factors, and detailed quantitative testing of ocular motor, vestibular, and postural functions) vs. clinical scores such as HINTS, ABCD2 for differential diagnosis of vestibular stroke and vestibular neuritis. Logistic Regression, Random Forest, Artificial neural network (ANN), and Geometric matrix completion (e.g., Single/ MultiGMC) were used where MultiGMC outperformed clinical scores. Random forest was used to rank features based on their discriminative power to understand the diagnosis better.

L. Masankaran et al. [34] use the DHI questionnaire to distinguish between BPPV types. Recursive Feature Elimination and Feature Importance with Extra Trees Classifier selected the Gaussian naive Bayes classifier that gave the best performance. Grözinger, Michael et al. [37] uses deep neural networks trained on DizzyReg [24] for diagnosing vestibular migraine and Meniere's disease in clinical practice. Strobl R et al. [64] used classification and regression trees to diagnose eight different vestibular disorders based on only eight critical variables from the DizzyReg dataset. Kim BJ et al. [65] compared various classification models such as SVM, logistic regression, random forest Catboost to differentiate between central and non-central causes of dizziness by using simple clinical information such as demographics, medical history, systolic and diastolic blood pressure, and heart rate. Additionally, the SHapley Additive explanations (SHAP) value was used to explain the importance of each variable in the clinical information for diagnosis. Exarchos TP et al. [25] consists of a recommendation tool to guide the general practitioners and experts and a diagnostic model for 12 balance disorders. It uses wrapper feature selection methods with decision trees enhanced with AdaBoost trained on a dataset with 350 features containing detailed patient information to create one binary model each for 12 different balance disorders. Richburg, Heidi et al. [38] suggests a survey-based support system for diagnosing BPPV, which does not require a physician interfacing with the software. It uses attribute selection filters and wrappers and decision trees on patient data collected through a questionnaire. Rasku J et al. [42] created a computerized peer support system for Meniere's disease program that can verify and assess the diagnosis of Meniere's disease by using a pattern recognition method.

Dynamic Uncertain Causality Graph (DUCG) [36] is a newly proposed Probabilistic Graphical Model, which can deal with systems with logic cycles, dynamics, and uncertainties. C. Dong et al. [39] proposes a novel diagnostic and reasoning modeling to identify among 22 etiologies based on investigations and relevant characteristics of vertigo using DUCG methodology. Dong, Chun-Ling et al. [40] uses a DUCG based differential diagnostic model for subtype differentiation of benign paroxysmal positional vertigo (BPPV). The symptoms, signs, findings of examinations, medical histories, etiology, and pathogenesis are incorporated in both diagnostic models. They manifest higher diagnostic correctness than other ML-based methods, good robustness to incomplete medical data, and provide a rationale for choosing a disease. Table 3 shows the results for studies done on other questionnaires and multimodal databases showing mean accuracy (Acc), mean specificity (Spec), mean sensitivity (Sens), and mean F1-score for all target classes. CV-Cross-Validation; BPPV-benign paroxysmal positional vertigo; MD-Menière's disease; VNE-Vestibular Neuritis; CL-Central lesion; ANE-Acoustic Neuroma, VP-Vestibular Paroxysmia, VM-Vestibular Migraine; t-BPPV-typical benign paroxysmal positional vertigo; a-BPPV- atypical benign paroxysmal positional vertigo; PPPD- persistent postural perceptual dizziness; UPD-unilateral peripheral dysfunction; BVD-bilateral vestibular dysfunction; AVS-Acute vestibular syndrome Nystagmus is often associated with vertigo. UVP-Unilateral Vestibulopathy; BVP- Bilateral Vestibulopathy, FD- Functional Dizziness.

Table 3: Performance on questionnaires and multimodal databases

Year	ML Algorithm	Target	Sample Size	Evaluation	Performance			
					Acc.	Sens.	Spec.	F1
2016 [25]	Decision trees enhanced with Adaboost + expert knowledge	ANE vs t-BPPV vs a-BPPV vs VP vs VM vs MD vs CL vs PPD vs VNE vs UPD vs BVD vs others	985	10-fold CV	82.65	81.61	83.6	-
2018 [38]	Decision tree	BPPV	45	45 training cases	92	88	95	-
	Gaussian Naive Bayes	BPPV	114	10-fold CV	73.91	-	-	72.73

2018 [34]	K-nearest neighbor(k=11)				69.57	-	-	69.68
	Support Vector machines-poly				65.22	-	-	64.53
	Random forest				65.22	-	-	65.35
2020 [37]	Deep neural networks	VM vs MD	346	10-fold CV	98.2	87.65	-	-
	Boosted Decision Trees				88.9	63.9	-	-
2020 [21]	Logistic regression	Vestibular stroke vs Peripheral AVS	40	5-fold CV	52	-	-	-
	Multi-Geometric matrix completion				82	-	-	-
2021 [65]	Support vector machine	Central vs non-central dizziness	3116	1310 test cases	-	99.2	11.6	-
	Logistic Regression				-	99.2	6.8	-
	Random Forest				-	99.2	6.0	-
	Catboost				-	100	4.6	-
2021 [64]	Classification and regression trees	MD vs BPPV vs VM vs UVP vs BVP vs VP	1066	10-fold CV	42.2	-	-	-

4.3 Machine Learning Applications to Nystagmus and Vestibulo-Ocular Reflex (VOR) Tests

Nystagmus is defined as an involuntary rapid and rhythmic movement of the eyeball and is often associated with vertigo. Amine Ben Slama et al. [30] proposed a Videonystagmography (VNG) based machine learning approach to identify vestibular neuritis. These investigators video-recorded nystagmus, used a pupil tracking algorithm to measure nystagmus metrics and then used Fischer criteria for feature selection and SVM for classification, which gave classification results higher than K-nearest neighbour and artificial neural network with an accuracy of 94.1%. BPPV can affect any one of the 3 semicircular canals, but most often affects the posterior or horizontal canal which can be identified with nystagmus patterns. Lim EC et al. [35] used a deep learning model trained on extracted image data from nystagmus videos induced by positional tests to classify the affected canal in BPPV patients. More recently a novel deep learning based framework involving convolutional neural networks was introduced for automatic detection of torsional upbeating nystagmus of PC BPV from nystagmus videos [66]. When tested on a clinically collected torsional nystagmus video dataset, the method showed promising results in frame-level identification of torsional motion and final torsional nystagmus segment localization which can help clinicians improve their diagnostic accuracy.

M. Juhola et al. [26] used a signal analysis technique on video head impulse tests which assess the vestibulo-ocular reflex to differentiate healthy subjects from those with vestibular loss affecting the semicircular canals. These investigators sought to separate controls from acoustic neuroma and used KNN, linear discriminant analysis, naive Bayes, SVM, k-means clustering, MLP network, Kohonen network, and decision trees, with decision trees yielding the best accuracy of 89.8% using decision trees. Table 4 shows the results for studies done on nystagmus data showing mean accuracy (Acc), mean specificity (Spec), mean sensitivity (Sens), and mean F1-score for all target classes. CV- Cross-Validation; VNE-Vestibular Neuritis; ANE-Acoustic Neuroma, PC-BPPV- posterior canal benign paroxysmal positional vertigo; HC-BPPV- horizontal canal benign paroxysmal positional vertigo; T-BPPV- torsional canal benign paroxysmal positional vertigo.

Table 4: Performance on Nystagmus data

Year	ML Algorithm	Target	Sample Size	Evaluation	Performance			
					Acc.	Sens.	Spec.	F1
2008 [26]	K-nearest neighbor(k=5)	ANE	44	10-fold CV	87.7	79.2	94.2	-
	Linear discriminant analysis				87.6	81.1	92.5	-
	Quadratic discriminant analysis				87	84.9	88.6	-
	Naive bayes				88.3	82.7	92.5	-
	K-means clustering (k=2)				85	78.2	90.2	-
	Decision trees				89.8	83.6	94.7	-
	multilayer perceptron networks (16 hidden nodes)				88.8	82.9	93.4	-
	Kohonen networks 7x7 nodes				87.6	78.9	94.2	-
	support vector machines (radial)				89.4	82.7	94.6	-
2019 [30]	K-nearest neighbor	VNE	60	5-fold CV	85.3	86.5	87.6	-
	Artificial neural network				86.8	88.3	89.5	-
	Fischer-support vector machine				94.1	93.2	95.9	-
2019 [35]	Convolutional neural network	PC-BPPV vs HC-BPPV vs T-BPPV	3457	10-fold CV	-	80.8	97.1	79.4
2021 [66]	Convolutional neural network	T-BPPV	8000	8:2 Train-Test Split	85.7	78.9	-	81.0

4.4 Machine Learning Applications to Posturography and Gait Features

To diagnose disorders related to human balance systems, clinicians sometimes use methods of recording body sway. Machine learning techniques applied to posturography and gait analysis parameters could potentially aid the diagnosis of balance disorders. Pradhan C et al. [27] used pattern recognition techniques on posturography and spatiotemporal gait data of 150 samples acquired on a gait mat to identify gait disorders. SVM and ANN differentiated the gait patterns with higher sensitivity and specificity compared to

KNN and NB. SVM reported highest results with 93% sensitivity and 97% specificity. Ahmadi, SA et al. [28] used static posturography signal patterns for automatic classification into eight disorders, including Parkinson's disease, phobic postural vertigo, acute vestibular syndrome, cerebellar disorders. KNN, SVM, ANN, logistic regression, random forest, and the extra forest were used for classification where extra forest performed better than others. An ensemble method (stacking classifier) combining all these classifiers gave the best performance. The t-Distributed Stochastic Neighbor Embedding (t-SNE) technique was used to plot the data into two dimensions that showed clear clusters of diseases. Ikizoglu, Serhat et al. [29] compared two feature selection techniques (T-test and Sequential Backward Selection) and two feature transformation techniques (Principal Component Analysis and Kernel Principal Component Analysis with Gaussian and polynomial kernels) for dimensionality reduction on data obtained from dynamic posturography to be used with SVM. Feature transformation techniques resulted in more accurate models, and dimensionality reduction helped in reducing the computation time.

S. Heydarov et al. [22] compared SVM, SVM with Gaussian kernel, and decision tree on gait data to classify vestibular system disorders and found SVM with Gaussian kernel to perform better than others. Krafczyk, Siegbert et al. [57] used ANN to classify four neurological and vestibular disorders based on static posturography characteristics with high overall sensitivity. Y Zhang et al. [44] proposed an SVM-based method for determining gait disturbances of BPPV by collecting data in clinical settings with the help of wearable accelerometers. The data was collected from 27 outpatients and 27 healthy subjects by observing different temporal-spatial and gait-specific variables while they walk wearing the sensor. The data collected was used for training SVM with a linear kernel with 5-fold cross-validation. This study suggests that wearable technologies are an excellent source for collecting data that can be used to train ML models for diagnosing vertigo and related illnesses. Such technologies interfaced with smart devices are easier to integrate within users' everyday routine and collect information at regular intervals. They reduce the need of clinical tests offering the users a remote environment to record their health data. Kamogashira T et al. [67] used ensemble algorithms such as gradient boosting classifier, bagging tree on center of pressure (COP) sway during foam posturography measured from patients with dizziness to predict vestibular dysfunction. Gradient boosting achieved 82% sensitivity followed by random forest and logistic regression with 81% and 78% sensitivity, respectively.

Table 5 shows the results for studies done on posturography and gait data showing mean accuracy (Acc), mean specificity (Spec), mean sensitivity (Sens), and mean F1-score for all target classes. VNE-Vestibular Neuritis; ANE-Acoustic Neuroma; PPV-phobic postural vertigo; CA-cerebellar ataxia; BV-bilateral vestibulopathy; PSP-progressive supranuclear palsy; OT-orthostatic tumor; DN Downbeat nystagmus; AVS- Acute unilateral vestibulopathy; PD-Parkinson's disease; PNP- Poly-neuropathy.

Table 5: Performance on posturography and gait data

Year	ML Algorithm	Target	Sample Size	Evaluation	Performance			
					Acc.	Sens.	Spec.	F1
2006 [57]	Artificial neural network	PV vs CA vs VNE	60	60 validation cases	-	93	93	-
	Artificial neural network		150	10-fold CV	-	90.6	96.1	-
	Support Vector Machine				-	93	97	-

2015 [27]	K-nearest neighbor	PPV vs CA vs PSP vs BV			-	73.3	92.3	-
	Naïve bayes				-	77	93.8	-
2017 [22]	Support vector Machine	Vestibular system disorders vs healthy	18	5-fold CV	75	-	-	-
	Support vector machine with gaussian kernel				81.3	-	-	-
	Decision tree				62.5	-	-	-
2019 [28]	K-nearest neighbor	OT vs PPV vs CA vs DN vs AVS vs PNP	293	50-fold CV	64.5	-	-	-
	Extra Forest				80.7	-	-	-
	Stacked classifier				82.7	-	-	-
2020 [29]	Support vector Machine-polynomial	Vestibular system disorders vs healthy	37	-	81.0	-	-	-
	Support vector Machine-gaussian				89.2	-	-	-
2020 [67]	Gradient Boosting classifier	Vestibular dysfunction vs healthy	238	5- fold CV	-	82	-	-
	Logistic Regression				-	78	-	-
	Random Forest				-	81	-	-

5. Discussion and Potential Directions

Could the integration of artificial intelligence into medical diagnosis significantly improve the speed and accuracy of diagnosis? The answers are unclear for several reasons. (1) Investigators have sometimes sought to answer a given diagnostic question without using the highest yield data (eg: diagnosing BPV with a questionnaire or with posturography when nystagmus profiles provide the answer). (2) seeking to separate large numbers of disorders rather than a few differential diagnoses for a single presentation. (3) Modern Laboratory Tests that diagnose specific vestibular disorders (vHIT for vestibular neuritis [68], ictal nystagmus for Meniere's Disease [69], VEMP for superior canal dehiscence [70]) have not been used in ML endeavors. The merits of increased AI usage in medical diagnosis include: (1) bringing machine learning expertise where human expertise is unavailable (2) reducing manual tasks and the freeing up of physician's time, (3) increasing efficiency and productivity by providing a scalable application.

Kim BJ et al. [65] applied ML algorithms on simple clinical information such as demographics and medical history obtained at early stages/emergency centers can perform a differential diagnosis for vertigo disorders. Such algorithms once optimised will greatly assist non-expert physicians treating vertigo in the frontline. There is a scope of using embedded systems with trained ML models to help in the early diagnosis of acute vertigo. Attribute weighting and selection methods, Bayesian networks, dynamic, uncertain casualty graphs, decision trees, random forests can help assess the relative importance of attributes for disease classification [39, 40, 59]. Lim EC et al. [35] suggest the possibility of using a deep learning architecture embedded on any device that can record eye movement to classify nystagmus types into subtypes of BPPV directly. Filippopulos, Filipp M. et al. [41] suggests using an AI-based computerized clinical decision support system with an easy-to-use mobile application and systematic expert support to improve diagnostic accuracy and outcomes of patients presenting with acute acute vertigo syndromes in primary care.

Existing studies that have utilized machine learning algorithms have highlighted the limited availability of large-size clinical datasets [38, 43]. Small sizes of clinical datasets and missing values in clinical records, such as demographics, medical history, and results from clinical tests, tend to reduce the performance of machine learning algorithms. Training on large clinical datasets is imperative for machine learning models to yield robustness and high classification results. High-dimensional data with multiple types of features such as demographics, patients' medical history, several clinical test results, increases the search space and algorithmic computation time. Various irrelevant features that do not contribute as an identification factor of a disease among such high-dimensional data need to be identified and excluded to reduce the feature-set dimension. Few studies have focused on feature extraction and feature transformation methods to reduce the feature-set dimension, achieving increased classification accuracy, also preventing overfitting [23, 29, 30]. The machine learning techniques in existing literature provide an automated procedure for disease prediction by interpreting complex clinical data, mainly resorting solely to model selection and parameter determination. It is important to focus on the underlying pathogenesis and pathophysiology instead of solely relying on machine learning classification models. Future studies should consider merging the intelligent diagnostic system with the physician's interpretation in clinical medicine.

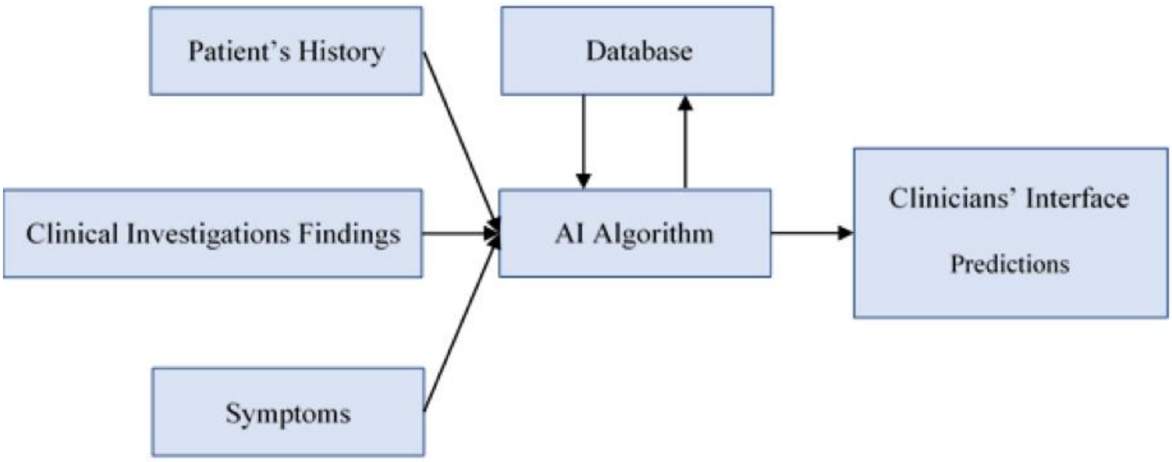

Figure 3: Suggested model of a diagnostic system.

The studies suggest that there is a need to develop a decision support system (DSS) that can cover a wide range of vertiginous diseases [38, 42, 65] which should be able to collect the input data into a database that may be later used to retrain models and improve accuracy. Figure 3 illustrates the suggested model of such a decision support system for disease diagnosis. The AI algorithm of the system maps the input data to the most plausible diagnosis. An ensemble of different machine learning models should work better than individual classifiers for predicting the disease. The DSS should also handle cases with incomplete clinical evidence either through extrapolating from the previous database or using methods capable of working with incomplete inputs, thereby achieving robustness and higher accuracies in vertigo classification

5. Conclusion

Vertigo is a common symptom arising from many etiologies ranging from benign to potentially severe. This paper summarises the use of modern artificial intelligence techniques in the differential diagnosis of acute vertigo. Despite the long history of using AI for neuro otological diagnosis, a superior diagnostic support system has not yet emerged. Publicly available datasets of patients with diverse vertigo presentations and the results of their interrogation with new, widely available audiovestibular tests are likely to encourage future researchers to undertake much-needed work in this domain.

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