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Review Article

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Current Artificial Intelligence Applications in Vertigo: A Review

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Abstract

Vertigo and dizziness symptoms affect approximately 20% of the population. With the increasing use of artificial intelligence (AI) in healthcare, AI applications have been developed to assess "vertigo and dizziness." A common approach in evaluating patients with these symptoms is to analyse the vestibule-ocular reflex (VOR). A review of the literature shows that data such as nystagmus evaluations, vestibular test results, and patient history are processed through AI methods-particularly deep learning models—to analyse data from patients experiencing dizziness. This study reviews current AI applications and outcomes in the field of vertigo and dizziness. The goal is to provide a summary of the studies and offer guidance for future research on the use of machine learning and AI in vertigo diagnosis. The applications being developed will streamline the differentiation between the central and peripheral causes of vestibular symptoms in high-demand areas such as neurology and otorhinolaryngology emergency departments. These advancements will enable more accurate and timely referrals and simplify vestibular assessments in audiology, otorhinolaryngology, and neurology clinics.

Keywords Artificial intelligence · machine learning · vestibular · vertigo · dizziness

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INTRODUCTION

The vestibular system plays a key role in maintaining spatial orientation and stabilising balance through visual reflexes. To achieve this, it converts the forces associated with head acceleration and gravity into biological signals sent directly to motor cortex for postural and ocular stability and to the cortex for aiding orientation. When functioning normally, we are unaware of these continuous processes. Unlike visual, auditory, or olfactory stimuli, the functionality of the vestibular system often goes unnoticed until something goes wrong (1). Vestibular dysfunctions can cause symptoms such as vertigo, spontaneous or triggered dizziness, imbalance, and oscillopsia.

Vertigo is the sensation of self-motion or the perception that objects in the environment are moving. Vertigo and dizziness symptoms affect approximately 20% of the population (2, 3). Dizziness is described as a disturbed sense of spatial orientation, imbalance, or lightheadedness. Oscillopsia is the perception that objects in the visual field are oscillating, which can arise in vestibulo-ocular reflex (VOR) dysfunction. Symptoms may occur spontaneously or be triggered (e.g., by certain positions, sound, or orthostatic changes) (3).

Clinicians may face challenges when dealing with patients with vestibular problems, largely because patients often struggle to articulate their symptoms. Vestibular dysfunctions are frequently labelled as dizziness, a nonspecific term that could also result from cardiac conditions, psychological disorders, medication side effects, and various other diseases. Vestibular diseases are broadly categorised into central and peripheral causes, with central causes being less common. Benign paroxysmal positional vertigo (BPPV) is the most common peripheral vestibular disorder. BPPV arises when crystals called otoconia dislodge from the otolithic macula beds and move into one or more semicircular canals, leading to dizziness attacks that can last from seconds to minutes. These episodes are usually characterised by a repeated sensation of environmental spinning, and repositioning manoeuvres are used for treatment (4). Another peripheral condition is Meniere's disease (MD), a clinical syndrome involving vertigo episodes, often accompanied by tinnitus, ear fullness, and fluctuating sensorineural hearing loss (5). Acute Unilateral Vestibulopathy, also known as vestibular neuritis characterised by a sudden onset of severe vertigo that persists for days and is often accompanied by nausea and vomiting (6). Vestibular migraine (VM), on the other hand, is based on recurring vestibular symptoms and a history of migraine, with acute attacks ranging from 5 min to 72 h in duration; VM should be considered a diagnosis of exclusion and requires a history of headaches that meet migraine criteria (7).

How is the vertigo diagnosed?

A thorough anamnesis and complete examination are essential for the correct diagnosis of patients with vertigo. Despite detailed assessments, reaching an accurate diagnosis can be challenging in some patients. In patients with vertigo, evaluating nystagmus-defined as rapid rhythmic eye movements observed during an episode-based on factors such as spontaneity/induction, direction, torsional nature, and fixation ability is important for differential diagnosis. Assessing nystagmus with these parameters requires knowledge and experience. Additionally, as the most identifiable function in vestibular patients is the VOR, many examinations are related to this reflex's assessment. Therefore, AI-assisted software could simplify the evaluation of nystagmus, providing guidance in the differential diagnosis of complex cases (8).

Artificial intelligence and healthcare applications

Artificial Intelligence (AI) is an information processing system that mimics high-level cognitive functions or autonomic behaviours characteristic of human intelligence. This system assists in various processes, including perception, learning, connecting multiple concepts, reasoning, problem-solving, communication, and decision-making. The first studies on artificial neural networks in AI were conducted by McCulloch and Pitts in 1943, demonstrating that any computable function could be calculated through networks of neurons and logical operations (9). Hebb later proposed a simple rule to modify the strength of the connections between neurons, making it possible to realise neural networks capable of learning (9).

AI is encountered in healthcare in areas such as early diagnosis, decision-making, treatment, and research. As a critical driver supporting the development and evolution of Industry 5.0, AI has become an essential component of healthcare advancements by combining human capabilities with technology. Early efforts to facilitate and improve diagnostic accuracy using computer-assisted programs by physicians date back to the 1950s. Notably, machine learning algorithms assist in differential diagnosis by considering numerous parameters and clinical features. This information can be used to optimise diagnostic criteria for many diseases, ease differential diagnosis, and improve patient follow-up (10, 11). With the increasing complexity and volume of healthcare data, the use of AI in this field has gained attention. AI is anticipated to significantly impact various areas of healthcare in the future and can improve many aspects of healthcare services. AI technologies are particularly known to be increasingly used in health-related areas such as early diagnosis, reaching accurate diagnoses, clinical decision-making, and maintaining health (12, 13).

Transfer learning is a machine learning technique that uses pre-trained models developed on extensive datasets and adapts them to target problems with limited data. This approach is particularly advantageous in medical applications, where data collection can be resource intensive. For example, pre-trained convolutional neural network (CNN) models, such as Google's EfficientNet or Microsoft's DeepSpeed, can be fine-tuned to analyse nystagmus data or videonystagmography (VNG) recordings, which are critical for vertigo diagnosis (14-16).

Given the limited availability of medical data for vertigo diagnosis, the AI tools developed by Microsoft and Google offer valuable solutions. These tools are designed to maximise performance in data-constrained environments and have significant potential for improving diagnostic accuracy.

Microsoft Azure Machine Learning AutoML: Automates the development of machine learning models, optimising them for complex clinical challenges like vertigo diagnosis (17).

Responsible AI Tools: Ensures model transparency and reliability, which is essential for clinical applications in neurology and otolaryngology (17).

TensorFlow Hub: Facilitates the adaptation of pre-trained models to specific tasks, such as analysing eye movement data from VNG (18).

TensorFlow Lite, optimised for resource-constrained environments, enabling real-time diagnostics on mobile and portable devices (18).

Google Vertex AI provides advanced AutoML capabilities for developing high-performance AI models with minimal data. This is particularly relevant for identifying subtle clinical patterns in vertigo-related cases (18).

Data Augmentation: Google's Albumentations Library supports data augmentation, enabling the generation of synthetic datasets to improve model training. For instance, augmented nystagmus video data can enhance the diagnostic model performance (19).

Few-Shot Learning: Techniques like OpenAI's CLIP or Google's BigGAN enable models to achieve high accuracy with minimal training data, making them ideal for clinical settings with limited datasets (20).

These technologies facilitate rapid diagnostic workflows in clinical environments, ensuring timely intervention for patients with vertigo, especially in high-demand areas like emergency departments (14, 21). Transfer learning and data augmentation techniques address the common challenge of small datasets in healthcare, improving diagnostic outcomes (20, 22). TensorFlow Lite and similar tools enable real-time analysis of patient data, such as nystagmus, through portable and mobile diagnostic devices (18).

The integration of transfer learning and modern AI technologies into vertigo diagnostics offers significant opportunities to overcome the challenges associated with limited clinical data. By using advanced tools developed by technology leaders such as Microsoft and Google, clinicians can achieve faster, more accurate, and cost-effective diagnoses. These approaches hold the potential to revolutionise the diagnostic process in neurology, audiology, and otolaryngology clinics, paving the way for more efficient and reliable patient care (14, 15, 21, 23).

Artificial Intelligence Applications in Vertigo

The first artificial intelligence application in the literature for patients with complaints of dizziness and vertigo was published in 1999. This involved the development of an oto-neurological expert system (ONE) aimed at assisting with the diagnosis of vertigo and creating a research database. The ONE database was designed to collect data on patient history, symptoms, and test results for diagnostic studies in patients with dizziness (24). The reasoning process was based on a pattern-recognition approach, achieving a 65% accuracy rate in diagnosis compared to human physicians, establishing it as a valid decision-maker. Various machine learning algorithms, including support vector machines (SVM), Naive Bayes (NB), decision trees (DT), K-nearest neighbours (KNN), neural networks (NN), and genetic algorithms, are used for classifying the types of vertigo (25). While neural networks offer advantages such as automatic feature extraction, resilience to data changes, scalability to large datasets, and adaptability to evolving problems, they also have drawbacks, including the need for extensive training data, high costs, lengthy processing times, and complexity in understanding their outputs (25). The artificial intelligence technologies used in vertigo are summarised in Table 1.

Literature review

This study aims to review and summarise research involving the use of artificial intelligence (AI) technology in vestibular diseases, providing an overview of current studies. In this review, Published studies were examined using the Database Access and Statistics System (VETIS) in Istanbul University's Online Library, entering the advanced search keywords "(artificial intelligence or machine learning or deep learning) AND (vestibular or vertigo or meniere or BPPV or dizziness)" in

Table 1. Artificial intelligence Technologies

Technology/Tool	Developer	Purpose/Application	Key features	Release date	Country of origin
Transfer Learning	The Machine Learning Community	Adapts models pre-trained on large datasets to address tasks with limited data (e.g., vertigo diagnosis), helping overcome data scarcity in medical applications.	Rapid adaptation, high accuracy with fewer samples, and reduced data requirements	-	Various
Microsoft Azure Machine Learning AutoML	Microsoft	Automates model development and optimisation for complex clinical challenges, such as vertigo diagnosis.	Automated model selection, hyperparameter tuning, and robust performance with limited datasets	2018	USA
Responsible AI Tools	Microsoft	Ensures the transparency and reliability of AI models in clinical settings (e.g., neurology, otolaryngology).	Model explainability, data security, and ethical compliance	2021	USA
TensorFlow Hub	Google	Facilitates the fine-tuning of pre-trained models (e.g., CNNs) for specific tasks, including nystagmus analysis and VNG-based vertigo diagnosis.	Rapid prototyping, extensive model library, and ready-to-use architectures for transfer learning	2018	USA
TensorFlow Lite	Google	Enables real-time diagnostics and analysis on resource-constrained devices (e.g., mobile or portable equipment).	Low latency, fast inference, suitable for edge deployment	2017	USA
Google Vertex AI	Google	Provides advanced AutoML capabilities for developing high-performance AI models with minimal data, crucial for detecting subtle clinical patterns in vertigo.	Integrated data management, streamlined training and deployment, and sophisticated automated model building	2021	USA
Data Augmentation (Albumentations Library)	Open-Source Community	Generates synthetic data to expand limited clinical datasets, improving the diagnostic model performance for vertigo.	Diverse data transformation techniques, mitigate overfitting, enhances model generalisation	2018	Various
Few-Shot Learning (OpenAI's CLIP, Google's BigGAN)	OpenAI, Google	Achieves high accuracy from minimal training examples, directly addressing data scarcity in vertigo diagnosis.	Effective learning with small datasets, flexible architectures, and high performance even with limited training data	2018/2021	USA
EfficientNet	Google	A pre-trained CNN-based model adapted to analyse nystagmus and VNG data, crucial for vertigo diagnosis.	Parameter-efficient architecture, high accuracy, optimised for transfer learning	2019	USA
DeepSpeed	Microsoft	A large-scale training framework adaptable to data-constrained clinical settings, such as vertigo diagnostics.	Distributed training, low latency, advanced optimisation techniques enabling high performance in data-limited environments	2020	USA

USA: United States

the search bar. The results of all publications are summarised in Table 2.

Table 2. The studies of artificial intelligence

Study	Institution	Patient count	Diagnosis	Assessment method	AI method	Purpose	Result
Wang et al. (23)	Royal Prince Alfred Hospital, Neurotology Clinic, Sydney, Australia	274	VM-160 MD-114	VNG, VHIT, VEMP, Caloric Test, Hearing Assessment	Python machine learning library	Distinguishing between MD and VM using an ML model	Accuracy: VM: 85.77%, MD: 97.81%
Lee et al. (14)	Yonsei University Wonju Severance Hospital	54	BPPV; 46 posterior, 9 lateral canal	VNG	ESA, AnyEye	Identifying nystagmus	Accuracy: 91.26%
Wu et al. (16)	Fudan University Eye and ENT HospitalChina	2671 training, 703 model	BPPV (RP, LP, L) and non-BPPV	VNG	CNN-BiLSTM-self-attention architecture	Identifying the affected canal or classifying as non-BPPV	AUROC: RP 0.991, LP 0.978, L 0.928
Chee et al. (26)	Singapore National Hospital, ENT	8	8 hypothetical dizziness scenarios	History and physical examination	OpenAI-ChatGBT	Predicting the correct diagnosis in scenarios	6/8 correct predictions
Lin et al.(27)	Taiwan Tertiary Hospital	64	Vertigo	vHIT	CNN	Predicting the hearing prognosis in patients with vertigo	Spearman Correlation: 0.553 (<0.001)
Mohan Baysal (28)	Parul University Institute of Medical Sciences and Research	100	Dizziness and vertigo	Clinical observation (unspecified)	CADINO-Diagnosis Tool	Predicting the relevant diagnosis	Accuracy: 84%
Ahmadi et al. (29)	Munich University Hospital	100	Central and Peripheral Vertigo	VOG, vHIT, Posturography, SVV	Perceptron (ANN)	Distinguishing between central and peripheral vertigo	Accuracy: 70%
Groezinger et al. (21)	German Vertigo and Balance Disorders Centre	1357	MD and VM	DizzyReg health data records	DNN	Classification algorithm for distinguishing between MD and VM	Accuracy: 91%, F-score 55%
Lim et al. (22)	Hallym University Medical School, ENT	1005	BPPV	Video goggles,, VOG	CNN	Identifying the horizontal, vertical, or torsional nystagmus and affected canal	Model Sensitivity: 0.91, Specificity: 0.91, Affected canal prediction Sensitivity: 0.80, Specificity: 0.97
Visscher et al. (30)	Swiss Concussion Centre	64	Vestibular and balance disorders present/absent	SOT, DVA, VEMPs, SVV, vHIT, Caloric test	The Statistics and ML Toolbox (MATLAB), SOM Toolbox	Clustering diagnoses based on symptoms	SOM improves AI-based diagnostic differentiation
Luo et al. (31)	Medical College of Wisconsin	868	Vestibular Disorders	Physician's Notes, Vestibular Anamnesis	Naïve Bayes	Predicting vestibular diagnoses via NLP + Naïve Bayes	Sensitivity: 93.4%, Specificity: 98.2%, ROC AUC: 0.995
Richburg et al. (32)	Medical College of Wisconsin	124	BPPV	Patient Survey	Decision trees and Wrapper methods	Creating a machine learning system for accurate BPPV classification	Accuracy: 0.69, Sensitivity: 0.71, Specificity: 0.67

Slama et al. (33)	Hospital of Habib Thamer-ENT	90	VN	VNG	Multi-Neural Network (MNN)	Developing an automated system for accurate vestibular neuritis diagnosis	Sensitivity: 93.66%, Specificity: 94.7%
Heydarov et al. (34)	Istanbul University-Cerrahpaşa Medical School	18	10 healthy 8 patients with Vestibular Disorder	Xsens MTW2 Wireless 3DOF Motion Tracker	SVM, SVM with Gaussian Kernel, Decision Tree	ML algorithm to detect vestibular system disorders	SVM with Gaussian Kernel: 81.3% accuracy
Priesol et al. (35)	Massachusetts Eye and Ear Infirmary	8080	Healthy or unilateral vestibular disorder	Caloric test, Rotational tests, VNG	ML-SVM	Improving the vestibular disorder diagnosis using ML	Accuracy: 76%
Adelsberger et al. (36)	University Hospital Zurich	16	7 healthy 9 BPPV	Romberg test, Tandem, 50-m walking test	SVM and kNN	Assessing the balance performance of BPPV patients before and after treatment	Accuracy: 88%
Dong et al. (37)	Beihang University, China	-	22 different disorders	Clinical data, Anamnesis	Dynamic uncertainty causality graph	Improving the diagnostic accuracy and supporting clinical decision-making	81.7% diagnostic accuracy (incomplete data), 88.3% (complete data)
Miettinen et al. (38)	Helsinki University Central Hospital	815	otoneurological diagnoses	anamnesis, Postrography, Caloric test, VNG	naïve Bayes	to use Bayesian probabilistic models for the accurate diagnosis of vertigo diseases	90% sensitivity, 92% positive predictive value, and 97% accuracy.
Varpa et. Al (39)	Tampere University Hospital in Finland	1283	Vertigo diseases	Otoneurological questionnaire, otoneurologic, audiologic, and imaging tests	k-NN and naïve Bayes classifiers	to assess a machine learning-based decision support system for diagnosing vertigo	Accuracy: 92%
Juhola et al. (40)	University of Tampere and Helsinki University Central Hospital	44	22 healthy 22 acoustic neuroma	VOR	Various ML	to compare different machine learning methods for classifying otoneurological diseases,	Accuracies: up to 89.8%
Figueria et al. (41)	Federal University of Sao Carlos, Brazil	247	118 healthy 129 central vestibular disorder	Electronystagmography; Saccade tests	constructive supervised neural network algorithms: Tower, Pyramid, and the DistAl algorithm	to use three constructive neural network algorithms to identify central vestibular system issues in patients	Accuracy : 91.4 (ID 8 network)
Tossavainen et al. (42)	University of Tampere, Finland, and Hearing Centre of the Tampere University Central Hospital	110	33 healty 77 MD	Posturography	ML	to develop an integrated system that enables the use of visual and mechanical perturbations for the clinical investigation of balance and visual-vestibular interactions	Accuracy: 80%
Kohigashi et al. (43)	Kyoto Institute of Technology, Japan	-	BPPV	3D eye movement simulator	AI (unspecified)	to develop an image-based computer-assisted system for diagnosing BPPV.	High Accuracy

Juhola et al. (44)	Department of Computer Science, University of Tampere and Helsinki University Central Hospital	564	MD:243 Vestibular schwannoma:128 BPPV: 59 VN :60 Traumatic vertigo : 53 Sudden deafness 21	Anamnesis, audiometry, and vestibular function tests. MRI	ML; neural networks, decision trees, and genetic algorithms.	to apply machine learning methods, such as decision trees, genetic algorithms, and neural networks, for diagnosing otoneurological diseases	True positive detection: The neural network : 87% the decision tree 90% Genetic algorithm 88%,

BPPV; Benign Paroxysmal Positional Vertigo; VNG, Videonystagmography; RP, right posterior canal; LP, left posterior canal; L, lateral canal, SOT; Sensory Organisation Test, SVV; Subjective Visual Vertical; VEMPs, Vestibular Evoked Myogenic Potentials; vHIT, Video Head Impulse Test; VOG, Videooculography; VM, Vestibular Migraine; VN, Vestibular Neuritis; MD, Ménière's Disease; CNN, Convolutional Neural Networks; ANN, Artificial Neural Networks; DNN, Deep Neural Networks, ML; Machine Learning; kNN, k-nearest neighbour; SVM, Support Vector Machine; AI, Artificial Intelligence; SOM, Self-Organising Map, et al.;. colleagues.

Wang et al. explored how machine learning models can aid in differentiating the causes of recurrent spontaneous vertigo. The study included VM and MD cases from a neurology clinic, using VNG and four different evaluation tests (vHIT, vestibular evoked myogenic potentials, caloric test, and audiogram) (23). Ten machine learning algorithms were used to develop classification models, simulating three clinical settings (neurology clinic, general neurology, and primary care) with varying data availability. The models effectively differentiated the two disorders with accuracies ranging from 85.77% to 97.81%. The AdaBoost and Random Forest models showed the best performance, achieving 97.81% accuracy in tier 1 and 92.34% in tier 3. History, VNG, vHIT, and caloric test were identified as the optimal feature subsets, with history as the top feature.

Lee et al. conducted a study on one of the most common vestibular disorders, BPPV. Evaluating nystagmus accurately is essential for diagnosing BPPV, which requires clinical experience and expertise (14). Videonystagmography (VNG), a non-invasive technique, is widely used in the diagnosis of BPPV. The study compared a convolutional neural network (CNN)-based nystagmus detection system, ANyEye, with VNG data, showing that ANyEye outperformed other eye-tracking methods, achieving a 91.26% accuracy rate. The dataset included infrared videos recorded via VNG from 46 patients with posterior and 9 with lateral semicircular canal BPPV, retrospectively obtained from Yonsei University Wonju Hospital. Initially, ANyEye identified the pupil using a CNN model approach, then the spine model was adapted to spatial test data features. Implemented in Python 3.6.8 using the Pytorch framework, the algorithm achieved a 91.26% detection rate within a 5-pixel margin of error and an error rate of 2.05±2.01, showing superiority over other algorithms in detecting nystagmus.

Wu et al. proposed a composite 1D and deep learning (DL) model for BPPV. For the study, they divided patients into two groups: one for model development and another for evaluating real-world generalizability (16). Eight features, including two headlines, three eye lines, and the slow-phase velocity (SPV) of nystagmus, were used as inputs. The study included 2671 patients in the training cohort and 703 in the test cohort. The hybrid DL model achieved an area under the receiver operating characteristic curve (AUROC) of 0.982 (95% CI 0.965, 0.994) for the overall classification, with the highest AUROC observed for the right posterior BPPV (0.991) and left posterior BPPV (0.979). Lateral BPPV had the lowest AUROC at 0.928. SPV was identified as the most predictive feature. The study designed DL models capable of accurately detecting BPPV subtypes and enabling rapid diagnosis in clinical settings.

Chee et al. conducted a study to evaluate ChatGPT's ability to identify vestibular causes of dizziness (26). ChatGPT was presented with eight hypothetical scenarios containing various clinical presentations and warning signs. Its responses were assessed based on consistency, clarity, coherence, accuracy, relevance, and recognition of limitations. ChatGPT provided consistent and logical responses, correctly diagnosing both vestibular and non-vestibular dizziness causes in six of the cases, although some limitations were noted. While ChatGPT demonstrated potential in distinguishing atypical dizziness and suggested further investigation steps for a clearer diagnosis, the study emphasised the limitations in its ability to address specific nuances in clinical decision-making. Nonetheless, the paper highlighted that AI would likely advance further within the field of medicine.

Lin et al. used artificial neural networks to classify the hearing prognosis in patients with sudden sensorineural hearing loss accompanied by vertigo (27).

The cohort, consisting of 64 patients treated with high-dose steroids, focused on examining the effect of vHIT on hearing prognosis. The measurement of high magnitude-squared wavelet coherence (MSWC) determined that the posterior semicircular canal with the highest coherent frequency was associated with full hearing recovery.

Mohan B. et al conducted a study on CADINO, a computer-aided diagnosis system in neurotology developed in India, evaluating its accuracy, educational utility, functionality, and effectiveness (28). Conducted with 70 patients, 24 simulated cases, and 6 case reports, the study also included pre- and post-consultation feedback from clinicians. The overall diagnostic accuracy of CADINO was found to be 86%, with a higher accuracy rate among specialists (84-80%) compared to trainees (57%). Many clinicians found CADINO valuable in patient management and educationally beneficial. The system is seen as having significant potential for rural and remote areas where access to neurotology services is limited, enhancing clinician knowledge and cognitive skills and improving patient safety and assessment quality.

Ahmadi et al. investigated the performance of standard and machine learning (ML) approaches in classifying patients with acute central or peripheral vestibular disorders, which can be challenging to differentiate in emergency settings (29). Forty stroke patients with vestibular complaints (19 with acute vestibular syndrome (AVS) and 21 without) and 68 patients with vestibular neuritis experiencing AVS were included in the study. All patients underwent a comprehensive neuro-otologic evaluation, including video oculography (VOG) and posturography, during the acute symptomatic phase, followed by magnetic resonance imaging (MRI) within 7 days of symptom onset. Diagnostic performance scores, including HINTS (Head Impulse, Nystagmus, Test of Skew Deviation) and ABCD2 (Age, Blood Pressure, Clinical Features, Duration, Diabetes), were compared to various ML approaches, such as logistic regression (LR), random forest (RF), artificial neural networks, and geometric deep learning models (Single/MultiGMC). Results indicated that ML methods, especially MultiGMC, outperformed univariate scores like HINTS and ABCD2 in distinguishing vestibular strokes from peripheral AVS (MultiGMC AUC: 0.96, HINTS/ABCD2 AUC: 0.71/0.58). HINTS performed comparably to MultiGMC in identifying vestibular stroke with AVS (AUC: 0.86) but showed poorer performance for vestibular stroke without AVS (AUC: 0.54). ML models learned to weigh clinically relevant features differently. Established ML methods such as RF (non-linear) and LR (linear) were noted as less robust classifiers (AUC: 0.89 vs. 0.62).

Groezinger et al. highlighted the potential of machine learning to aid in distinguishing between vestibular migraine and Meniere's disease (21). In their study, they used DizzyReg a clinical application that records the history, examination findings, test results, diagnosis, and treatment information of patients with dizziness and vertigo. Data were collected through the review of medical reports and surveys. Of the 1357 patients included, 9.9% were diagnosed with Meniere's disease and 15.6% with vestibular migraine. A deep neural network model achieved accuracy of 98.4±0.5%, sensitivity of 96.3±3.9% for vestibular migraine, and accuracy of 98.0±1.0% and sensitivity of 90.4±6.2% for Meniere's disease. The study emphasizedthat modern machine learning methods can form the basis for systems to assist practitioners and clinicians in decision-making for daily treatments.

Lim et al. used CNN with video-oculography (VOG) data to diagnose the affected canal in BPPV cases (22). They trained the CNN using a dataset with 3566 horizontal, 2068 vertical, and 720 torsional movements from 1005 BPPV patients. Each video clip was labelled according to the positional test it was recorded under (e.g., Dix-Hallpike, supine roll, head-hanging tests). After preprocessing with the circular Hough transformation for pupil identification and torsional movement measurement, the CNN achieved an overall accuracy of 0.800±0.008 with an area under the curve (AUC) of 0.901±0.008 for the final diagnosis. Horizontal and vertical nystagmus showed high accuracy, whereas torsional nystagmus had lower sensitivity and specificity due to insufficient characterisation.

Visscher et al. conducted a retrospective cluster analysis on balance and vestibular diagnostic data in patients with a history of concussion, aiming to reveal insights into phenotypic differences among patients independent of diagnosis (unsupervised learning) (30). The Calinski-Harabasz criterion was used to estimate the optimal number of clusters in the patient database. Two clustering methods were employed: the complex self-organising map (SOM) and standard k-means clustering, with SOM providing stable clustering, dividing patients into two groups: Group-1 (n=38) and Group-2 (n=58). Caloric test results indicated a substantial, statistically significant difference in slow-phase maximum velocity between the two groups, with Group-1 scoring 30.7% lower than Group-2 (27.6 [18.2] vs. 51.0 [31.0]). Group-1 also scored significantly lower on the sensory organisation test composite score (69.0 [22.3] vs. 79.0 [10.5]), while visual acuity (-0.03 [0.33] vs. −0.14 [0.12]) and dynamic visual acuity were higher (0.38 [0.84] vs. 0.20 [0.20]). Symptoms such as headache, blurred vision, and balance issues were reported more frequently in Group-1 than in Group-2 (>10%

difference). The study concluded that SOM could assist in the diagnostic process by clustering patients based on distinct vestibular impairment and balance profiles, offering a new perspective for managing complex, multi-dimensional pathologies. Overall, this retrospective study introduced a novel tool for identifying a subgroup of patients with distinct vestibular deficits in a concussion population using an unsupervised ML algorithm (multilayer, self-organising map). Caloric and dynamic visual acuity tests were found to be critical in defining the two groups.

Luo et al. analysed linguistic patterns in clinical documents written by clinicians regarding vestibular patients (31). Using natural language processing (NLP) and machine learning, this study investigated the predictive power of language usage in identifying vertigo types. The analysis demonstrated that the specific words used by clinicians could predict vestibular diseases with high accuracy. The results suggest that incorporating these linguistic patterns into clinical decision support systems could aid in accurate diagnosis.

Richburg et al. focused on differentiating between Posterior Canal (PC-BPPV) and Horizontal Canal (HC-BPPV) Benign Paroxysmal Positional Vertigo (BPPV) using the Dizziness Handicap Inventory (DHI) (32). Machine learning techniques were applied to analyse DHI features and assess their role in diagnosis using various algorithms, including Random Forest, Support Vector Machine (SVM), K-Nearest Neighbours, and Naïve Bayes. The Gaussian Naïve Bayes model achieved the best performance with an accuracy of 73.91%, a precision of 66.67%, a sensitivity of 80.00%, and an F1-score of 72.73%. However, the study noted the model's limited accuracy and emphasised the importance of considering patients' medical histories and nystagmus observations for diagnosis. The study suggested that future research should include more data and features to improve model performance and reduce overfitting issues.

Slama et al. introduced an artificial intelligence-based automated system for diagnosing vestibular neuritis (VN) (33). The study employed a pupil detection algorithm and an active contour model to ensure the accurate segmentation of nystagmus parameters. This method reduced the processing time through rapid segmentation, and the extracted parameters were reduced into a smaller dataset using Principal Component Analysis (PCA) before training a Multi-Neural Network (MNN). The trials achieved high accuracy.

Heydarov et al. developed a machine learning (ML) algorithm leveraging sensory information to detect vestibular system disorders (34). The study compared three ML methods-Support Vector Machine (SVM), SVM with Gaussian Kernel, and Decision Tree-to determine the most accurate approach. These methods were applied to data collected from both healthy individuals and patients with vestibular disorders. The evaluation of a dataset having 22 features found that the SVM with the Gaussian Kernel yielded the highest accuracy at 81.3%. The study also performed feature addition and removal, observing that some features significantly contributed to the overall accuracy. Feature selection methods were applied to identify the most distinctive features and reduce algorithm complexity while increasing accuracy (34).

Priesol et al. investigated the application of machine learning algorithms in evaluating the accuracy of vestibular tests for diagnosing dizziness and imbalance (35). Analysing data from 8080 patients, the study assessed caloric and rotational chair test data to diagnose vestibular hypofunction. The findings highlighted that the machine learning algorithms improved the test validation, with rotational time constant analysis providing higher sensitivity (85%) and specificity (90%) than other tests. These findings demonstrate that machine learning methods can enhance the identification of vestibular system damage.

Adelsberger et al. measured the balance performance in BPPV patients before and after treatment using the Romberg test with electronic insoles (36). This type of data analysis holds the potential for more advanced disease diagnosis and treatment monitoring through artificial intelligence and machine learning techniques.

Dong et al. proposed a model based on the "Dynamic Uncertain Causality Graph" (DUCG) to support vertigo diagnosis (37). The model used symptom and medical history data to achieve high accuracy despite missing or uncertain information. The system's inference process was visualisable, making diagnoses more comprehensible and convincing. The DUCG-based system achieved an accuracy of 81.7% with incomplete medical information and 88.3% with complete information. Clinical trials demonstrated the method's effectiveness and reliability as a diagnostic tool.

Miettinen et al. examined the efficient application of Bayesian methods in classifying neuro-otological diseases (38). Using 38 neuro-otological symptoms, the study applied Naïve Bayesian probabilistic models and Bayesian networks. Ten-fold cross-validation tests yielded an average sensitivity of 90%, a positive predictive value of 92%, and an accuracy rate of 97%. These results outperformed previously used artificial neural networks, highlighting the strong potential of Bayesian methods in accurately classifying neuro-otological cases.

Varpa et al. developed a decision support system for diagnosing vertigo disorders. The study integrated machine learning-derived information with expert knowledge to enhance the classification accuracy (39). Feature weighting significantly impacted the classification performance, and the knowledge discovery method was compared with the 1-NN, 5-NN, and Naïve Bayes classifiers. The combination of machine learning and expert insights yielded the highest accuracy.

Juhola et al. explored the classification of patients with vertigo and balance disorders versus healthy individuals using machine learning methods (40). Various classification techniques were tested, with decision trees and SVM achieving the highest accuracy rates of 89.8% and 89.4%, respectively, outperforming other methods by 1-5% (40).

Figueria et al. investigated three supervised artificial neural network algorithms-Tower, Pyramid, and DistAl-for identifying potential central vestibular system disorders using saccade test data (41). The study also presented the results obtained through the Backpropagation method. The goal of these algorithms was to shape the neural network architectures during training, achieving accurate classifications.

Tossavainen et al. developed a system facilitating clinical research on balance and visual-vestibular interaction (42). The system combined virtual reality visual stimulation with posturography on a force platform mounted on a motion platform. In a classification task involving 33 healthy controls and 77 patients with MD, the system found significant differences in stabilogram-derived parameters between patients and controls. The tests achieved slightly above 80% classification accuracy.

Kohigashi et al. developed a computer-aided diagnostic system for BPPV by analysing nystagmus responses from eye movement image sequences (43). The system simulated BPPV conditions using a balance control simulator and a 3D eye movement simulator, storing nystagmus responses in a database. Patient data were matched with simulations to predict BPPV causes and conditions. Tests on two patients demonstrated the system's diagnostic accuracy and validity.

Juhola et al. aimed to apply machine learning methods in disease diagnosis, analysing six disease classes (Meniere's disease, vestibular schwannoma, benign positional vertigo, vestibular neuritis, traumatic vertigo, and sudden hearing loss) (44). Neural networks, decision trees, and genetic algorithms were used, with the neural networks achieving 87% accuracy, the decision trees 90%, and the genetic algorithms 88%. The study found Meniere's disease and vestibular schwannoma to be well-detected.

CONCLUSION

The use of AI in healthcare applications is rapidly increasing (45-47). AI-driven algorithms are emerging to aid in differentiating vertigo diagnoses, particularly using nystagmus data to support differential diagnosis. Expanding ML algorithms to integrate non-vestibular balance parameters, such as trauma history, neuropsychological data, and cervical spine evaluation, may enhance the differential diagnosis accuracy for more complex subgroups.

Correctly distinguishing eye movements unrelated to nystagmus can be challenging, and future studies might benefit from networks that self-train on data-based subgroups of vestibular issues, including recovery times and specific treatment responses. Combining and refining neurological and otological examination algorithms could lead to comprehensive AI applications capable of distinguishing central from peripheral vertigo. With the development of vertigo-specific datasets and self-learning networks, the diagnostic and decision-making capabilities could be further improved. Multicenter studies could expand the data used for network training, increasing AI accuracy in practice (8, 25).

This article reviewed studies on modern AI techniques in vestibular system diagnostics. It encouraged future research on vertigo patient data from public datasets, using commonly applied vestibular and audiological assessments. Particularly, cases of benign paroxysmal positional vertigo (BPPV) that are challenging to identify, such as cupulolithiasis or lateral canal BPPV, could be expanded for more thorough evaluations. Additionally, the development of algorithms to aid in differentiating central from peripheral causes in neurology and otolaryngology emergency settings and audiology clinics could lead to AI applications that expedite accurate diagnosis and treatment.

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