Modern education and development
ISSN: 3060-4567

ANALYSIS OF METHODS FOR THE CLINICAL DIAGNOSIS OF VESTIBULAR DISORDERS BASED ON ARTIFICIAL INTELLIGENCE

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Abstract. *Vestibular disorders, which manifest as dizziness (vertigo) in clinical practice, pose a challenge for differential diagnosis. While modern instrumental examinations (VNG, vHIT, VEMP, posturography) have increased diagnostic accuracy, the multidimensional and complex nature of the data complicates clinical decision-making. The study involved observations of 196 patients treated at the Departments of Otorhinolaryngology and Neurology of the Multidisciplinary Clinic of Tashkent State Medical University between 2024 and 2026. This article analyzes the potential for clinical diagnosis of benign paroxysmal positional vertigo (BPPV) and vestibular migraine using artificial intelligence (AI), including algorithmic models, their sensitivity and specificity indicators, and issues of clinical integration.*

Keywords: *vestibular disorders, BPPV, vestibular migraine, artificial intelligence, differential diagnosis.*

Introduction. Vestibular disorders are among the common pathologies in otorhinolaryngology and neurology. This study thoroughly investigated the significance of benign paroxysmal positional vertigo (BPPV) and vestibular migraine as underlying causes in a substantial portion of patients presenting with complaints of dizziness.

BPPV is a mechanical disorder of the peripheral vestibular system caused by the displacement of otoliths into the semicircular canals. In contrast, vestibular migraine develops based on central pathophysiological mechanisms and often does not show clear changes in instrumental examinations.

Since these two pathologies manifest with clinically similar symptoms (vertigo, nausea, instability), differential diagnosis is a significant challenge.

Artificial intelligence systems can improve diagnostic accuracy by analyzing large volumes of clinical and instrumental data. Vestibular disorders are considered a common problem in modern clinical practice. Their primary symptoms - dizziness (vertigo), loss of balance, nausea, sometimes vomiting, and instability - significantly impact patients' quality of life. In clinical practice, approximately 20-30% of patients presenting with dizziness are found to have pathologies of the inner ear, including benign paroxysmal positional vertigo (BPPV), vestibular neuritis, Meniere's disease, and vestibular migraine (Neuhauser et al., 2005; von Brevern et al., 2015). At the same time, central nervous system pathologies, such as cerebellar stroke or multiple sclerosis, can also present with vestibular symptoms. As the patient's symptoms in these conditions are clinically similar, differential diagnosis is a complex task in practice.

Benign Paroxysmal Positional Vertigo (BPPV) and vestibular migraine are among the most common clinical vestibular disorders. BPPV arises from a mechanical disruption of the peripheral vestibular system; its primary pathophysiological mechanism is the displacement of otolith crystals into the semicircular canals. Clinical signs manifest as short-term, intense vertigo and a typical torsional nystagmus when the head is turned to a specific position. In contrast, vestibular migraine is associated with the central vestibular system and is often characterized by prolonged dizziness, a history of migraines, photophobia, and phonophobia. Both pathologies significantly impact a patient's quality of life, and establishing a clear clinical distinction between them can sometimes be challenging (Lempert & Neuhauser, 2009).

Although existing clinical diagnostic tools are useful for differentiating between BPPV and vestibular migraine, they sometimes lack sufficient accuracy. For instance, the Dix-Hallpike test increases sensitivity in detecting BPPV, but errors can occur if there is an atypical nystagmus associated with central vertigo. Furthermore, the diagnosis of vestibular migraine is often based solely on clinical criteria, as instrumental examinations (VNG, vHIT, VEMP) do not consistently yield pathological results. This can lead to misdiagnosis and, consequently, improper treatment for patients.

From this perspective, artificial intelligence (AI) systems are opening new possibilities in the diagnosis of vestibular disorders. AI-based systems can integrate large volumes of clinical and instrumental data and, by analyzing them, significantly increase diagnostic accuracy (Blanco et al., 2021). For instance, by deeply analyzing video nystagmography (VNG) images, convolutional neural networks (CNNs) enable the automatic detection of BPPV. Similarly, in central pathologies such as vestibular migraine, differential diagnosis becomes more precise by integrating multifactorial clinical parameters (duration of vertigo, migraine history, trigger factors) using machine learning algorithms (Ebenstein et al., 2022).

One of the main advantages of artificial intelligence is its ability to reduce subjectivity and prevent diagnostic errors. In clinical practice, patients' symptoms and test results may be interpreted differently by various doctors, which reduces the reliability of the diagnosis. AI, however, analyzes all incoming data based on a consistent standard, thereby improving the quality of diagnostics. Furthermore, AI systems expand the capabilities of telemedicine and remote consultation, which is particularly relevant for patients living in remote areas.

Another crucial aspect of diagnosing vestibular disorders using AI is the ability to integrate multimodal data. Clinical symptoms, VNG and vHIT results, VEMP indicators, audiometry, and even functional MRI images can be combined into a single model. This helps not only in identifying peripheral or central vestibular pathology but also in creating an individual risk profile for the patient. For example, it is possible to determine the canal type and otolith location in patients with BPPV, and for patients with vestibular migraine, a predictive model can be created based on symptom duration and trigger factors (Thompson et al., 2020).

In scientific literature, there are several studies on the differential diagnosis of BPPV and vestibular migraine using artificial intelligence systems. When diagnosing BPPV with CNN and Random Forest algorithms, sensitivity was recorded at 88-92% and specificity at 85-90%. For vestibular migraine, gradient boosting algorithms, which combine clinical parameters and instrumental test results, have demonstrated a diagnostic accuracy of over 80%. This indicates that the integration of AI systems into clinical practice is not only possible but also necessary (Blanco et al., 2021; Ebenstein et al., 2022).

Furthermore, AI systems accelerate the diagnostic process. The traditional differential diagnosis process is time-consuming because physicians compare results after performing various tests. In contrast, AI systems analyze all incoming data in real-time and suggest diagnostic options based on probability. This enables a quick and accurate diagnosis for patients, simplifies the physician's work, and reduces the likelihood of improper treatment.

At the same time, the importance of diagnosing vestibular disorders using AI is also reflected in the global healthcare system. Among patients presenting with dizziness, misdiagnosis and incorrect treatment result in years of health problems, a decreased quality of life, and economic losses. AI-based diagnostic systems mitigate this risk and direct patients toward the appropriate treatment.

From this perspective, the differential diagnosis of vestibular disorders, particularly BPPV and vestibular migraine, is of scientific and practical importance as a pressing issue, given that they manifest with clinically similar symptoms. The potential for artificial intelligence systems to improve diagnostic accuracy by analyzing large volumes of clinical and instrumental data opens a new paradigm for solving this problem. This can be applied not only in ENT and neurology clinics but also within the global telemedicine system.

Research Materials and Methods

The study was conducted from 2024 to 2026 at the Otorhinolaryngology and Neurology departments of the Multidisciplinary Clinic of Tashkent Medical Academy. Clinical observations were organized in a prospective design and were carried out through a comprehensive assessment of the patients' vestibular system status, analysis of instrumental examination results, and the integration of artificial intelligence (AI) models into the clinical diagnostic process.

A total of 196 patients were enrolled in the study, of whom 102 (52.0%) were women and 94 (48.0%) were men. The average age of the study participants was 44.8 ± 12.5 years. Patients with congenital or symptomatic labyrinthine diseases, injuries to the auditory organ, or damage to the central nervous system were excluded from the study.

The study was conducted in three stages:

1. Clinical-evolutionary stage - The patients' medical history, complaints, and data from physical and vestibular functional examinations were collected.
2. Instrumental-analytical stage - Vestibular responses were recorded using modern instrumental tests (VNG, vHIT, VEMP, posturography).
3. Algorithmic modeling stage - The collected data were input into artificial intelligence modules, and the sensitivity and specificity metrics of AI algorithms in differential diagnosis were evaluated.

The ocular and vestibular reflex activity of the patients was assessed using videonystagmography (VNG). The tests were conducted by recording the horizontal and vertical nystagmus components. Using posturography, the patients' center of pressure (COP) displacement parameters were determined and analyzed through a dynamic stabilometry algorithm.

Table 1. Demographic characteristics of the patients included in the study

Indicators	Total (n=196)	BPPV (n=104)	Vestibular Migraine (n=92)
Mean age (years)	44.8 ± 12.5	45.2 ± 10.9	44.3 ± 13.1
Number of women (%)	52.0	57.7	45.6
Number of men (%)	48.0	42.3	54.4
Mean symptom duration (months)	8.6 ± 4.1	6.2 ± 3.9	10.8 ± 4.3

The examination results of all patients were stored digitally in Microsoft Excel and SPSS Statistics 27.0. For the AI analysis, custom algorithms were developed based on the Python (v3.11) environment and the Scikit-learn, TensorFlow, and XGBoost libraries.

Table 2. Diagnostic performance of AI models (test set results)

Model Type	Sensitivity (%)	Specificity (%)	AUC (ROC)	Average Precision (%)
Logistic Regression	82.1	79.4	0.86	80.3
SVM (RBF kernel)	85.7	81.0	0.89	83.2
Random Forest	89.2	87.8	0.93	88.3
XGBoost	92.4	90.5	0.96	91.5
ANN (3-layer)	91.1	88.0	0.94	89.6

To present the results in a medically intelligible format for physicians, SHAP (SHapley Additive exPlanations) values were calculated. The following were identified as the 5 most important variables:

1. VOR gain (right posterior canal)
2. cVEMP amplitude asymmetry
3. Spontaneous nystagmus frequency
4. Presence of migraine
5. Posturographic COP sway area

Each participant received verbal and written information about the purpose of the study. The study was approved by the Bioethics Committee of the Tashkent Medical Academy (protocol No. 04/2024).

Table 3. Comparison of key diagnostic parameters between the BPPV and vestibular migraine groups

Parameter	BPPV (n=104)	Vestibular migraine (n=92)	p-value
Spontaneous nystagmus frequency (Hz)	1.8 ± 0.7	1.1 ± 0.6	<0.01
VOR gain	0.82 ± 0.06	0.93 ± 0.05	<0.001
cVEMP amplitude (µV)	122 ± 38	108 ± 42	0.04

COP dispersion (cm2)	15.4 ± 3.6	18.1 ± 4.2	0.02

At the conclusion of the study, an experimental mobile platform named "VestAI Diagnost" was developed based on the XGBoost model. When a physician inputs VNG, vHIT, and VEMP results, this system automatically provides differential diagnosis options within 3 seconds. During the testing phase, the system's clinical accuracy was 91.5%, with a misclassification rate of 8.5%.

Conclusion

This study found that analyzing vestibular pathologies with AI enhances the accuracy of clinical diagnostics and reduces subjective error, particularly in cases of BPPV and vestibular migraine. Integrating AI models with modern instrumental diagnostic tools can serve as an important guide for physicians.

The relevance of diagnosing vestibular disorders using AI is also reflected in the global healthcare system. Among patients presenting with dizziness, misdiagnosis and improper treatment can lead to years of health problems, a decreased quality of life, and economic losses. AI-based diagnostic systems mitigate this risk and direct patients toward the correct treatment.

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