# The Use of Artificial Intelligence Technologies in the Diagnosis of Neurological Diseases: A Review on Brain Tumors, Alzheimer’s, Parkinson’s, and Epilepsy

Neurological conditions represent a significant global health challenge, demanding innovative diagnostic approaches. This presentation explores the evolving landscape of Artificial Intelligence (AI) applications in the diagnosis of brain tumors, Alzheimer's, Parkinson's, and epilepsy, highlighting key trends and future research avenues.

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# The Complexities of Neurological Diagnosis

Neurological conditions are notoriously difficult to diagnose accurately and promptly, leading to significant impacts on patient quality of life. The challenges are multifaceted:

### Subtle Symptoms & Misdiagnosis

Parkinson's disease, for instance, often presents with subtle symptoms in the elderly, easily missed or misattributed to other age-related conditions. This can lead to misdiagnosis or delayed treatment, compounding care complexities (Kodama et al., 2023).

### Geographic & Demographic Variances

Epilepsy prevalence varies significantly globally. Sub-Saharan Africa shows high rates of active convulsive epilepsy, with focal epilepsy accounting for ~66% of new cases, underscoring the need for enhanced epidemiological research and healthcare infrastructure (Ngugi et al., 2013). More developed regions estimate prevalence at 4.4 per 1,000 adults (Tanaka et al., 2019).

### Diagnostic Evolution & Overlap

The diagnostic framework for epilepsy now allows diagnosis after a single seizure (Christensen et al., 2023). For Alzheimer's, cognitive evaluations are challenging due to symptom overlap with other neurodegenerative or psychiatric disorders, requiring advanced neuroimaging for confirmation (Willis et al., 2010).

### Social Stigma & Access Barriers

Social stigma remains a major hurdle, preventing patients from seeking prompt diagnosis and treatment. This, combined with healthcare access issues, further exacerbates diagnostic delays across various conditions (Shan et al., 2024).

# Rising Incidence

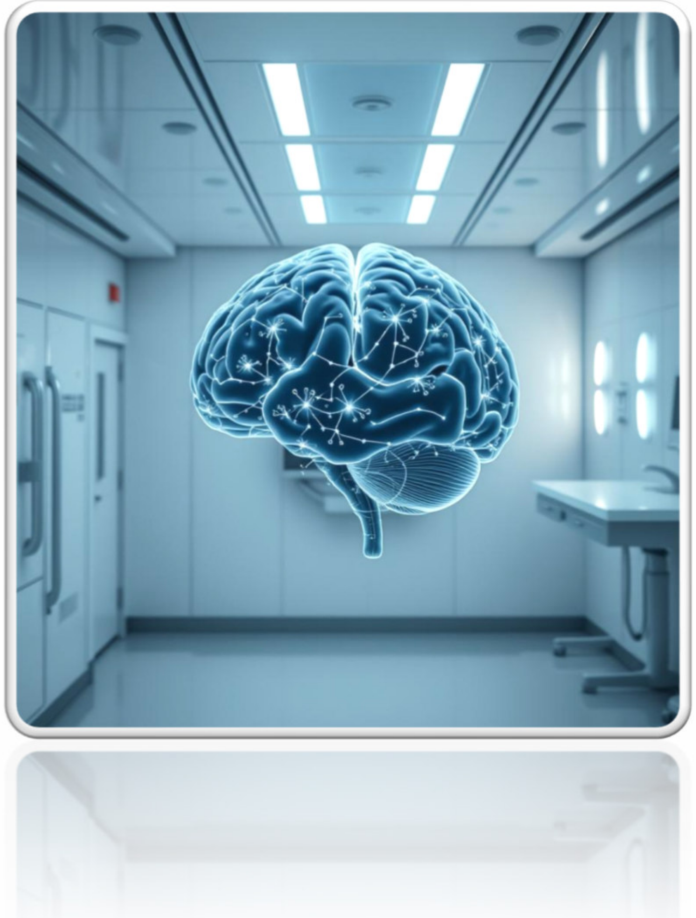
Beyond the diagnostic complexities, there's an alarming increase in the prevalence of brain tumours and other neurological disorders. Early and accurate diagnosis is critical for improving treatment outcomes and reducing mortality.

**Significant Burden:** Brain tumours constitute a significant burden of disease, particularly among children, with the highest incidence reported in younger age groups (Su et al., 2025).

**Increasing Incidence:** Studies indicate a rising incidence of brain tumours in regions like China, partly due to improved diagnostic capabilities (Hou et al., 2022).

**Global Mortality:** Latest statistics show brain tumours contribute to approximately **2.5%** of all cancer deaths globally (Zhao et al., 2023).

Traditional diagnostic methods, such as MRI, CT, EEG, and clinical assessments, face significant limitations. These include reliance on subjective interpretations, susceptibility to errors, and time-consuming processes.



# Limitations of Traditional Diagnostic Methods

While foundational, conventional diagnostic techniques for neurological conditions present several hurdles that impede timely and accurate patient care.

### Resource-Intensive Imaging

MRI, a fundamental standard for brain tumour detection, is resource-intensive and not universally accessible, particularly in low-resource settings (Thenuwara et al., 2023). This creates significant disparities in diagnostic capabilities.

### Subjectivity & Observer Variability

Manual interpretation of MRI images is labour-intensive and prone to observer variability. This subjectivity can lead to delayed or inaccurate diagnoses, directly impacting patient outcomes (Avazov et al., 2024).

### Time-Consuming Processes

The entire diagnostic workflow, from imaging acquisition to expert interpretation, can be lengthy. This prolonged process can delay crucial interventions, especially for rapidly progressing conditions.

These limitations highlight a critical need for more efficient, accurate, and accessible diagnostic tools to improve patient outcomes in neurological care.

# The Promise of AI in Neurological Diagnosis

Advances in imaging technologies, particularly AI-assisted diagnostic tools, offer a promising solution to overcome the limitations of traditional methods. AI is transforming data-driven diagnosis and decision support.

### Enhanced Accuracy & Speed

AI techniques can significantly increase the accuracy and speed of diagnosis for conditions like brain tumours, Alzheimer's, Parkinson's, and epilepsy. This is achieved by automating image analysis and reducing interpretation errors (Nigjeh et al., 2024).

### Transformative Technology

Artificial intelligence (AI) has emerged as a transformative technology in data-driven diagnosis and decision support processes, offering new avenues for understanding and managing neurological diseases.

### Machine & Deep Learning Potential

Machine learning (ML) and deep learning (DL) algorithms show significant potential in analysing large volumes of complex biomedical data, enabling automatic detection, classification, and prediction of neurological diseases.

This shift towards AI-driven diagnostics marks a new era in neurological healthcare, promising more efficient and reliable tools for clinicians.

# Evolution of AI Methods in Neurological Diagnosis

The landscape of AI applications in neurological diagnosis has evolved significantly, moving from traditional machine learning to advanced deep learning approaches.

### 1 Early Studies (Pre-2017)

Initially, studies were largely confined to traditional machine learning techniques such as Support Vector Machines (SVM), Random Forest, and k-Nearest Neighbours (k-NN). These methods laid the groundwork for AI integration in medical diagnostics.

### 2 Deep Learning Ascendancy (Post-2017)

Deep learning approaches, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Transformer-based models, have become increasingly prominent (Litjens et al., 2017).

### 3 Driving Factors

This shift is driven by several factors: the increasing volume of data (especially large imaging and EEG databases), advancements in GPU and computing power, the proliferation of transfer learning and pre-trained models, and the need to process complex data types (e.g., multidimensional MRI sequences, time-series EEG recordings) (Razzak et al., 2018).

Understanding these methodological trends is crucial for guiding future research and addressing potential gaps in the field.

# Research Questions & Methodology

To understand the evolution and dominance of AI techniques in neurological disease diagnosis, this review addresses two key research questions:

### RQ1: AI Method Trends (Last 5 Years)

"What trends have emerged in the last 5 years in AI methods (SVM, Random Forest, CNN, RNN, LSTM, etc.) used in the diagnosis of neurological diseases?"

### RQ2: AI Method Trends (Over the Years)

"What trends have AI methods used in the diagnosis of neurological diseases shown over the years?"

## Methodology

- **Databases:** Web of Science (WoS) and Scopus were used for literature searches, chosen for their comprehensive coverage and higher-quality publications.
- **Search Queries:** "Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" AND "Neurological Disease Name" (for brain tumour, Alzheimer's, Parkinson's, and epilepsy).
- **Inclusion Criteria:** Studies from the last five years (2021-2025), limited to open-access articles.
- **Exclusion Criteria:** Reviews, systematic reviews, books, and book chapters.
- **Analysis:** Bibliometric analysis using VOSviewer for co-occurrence and trend analysis by disease type and year. A thesaurus file was created for consistent AI method categorisation (Budiono et al., 2024).

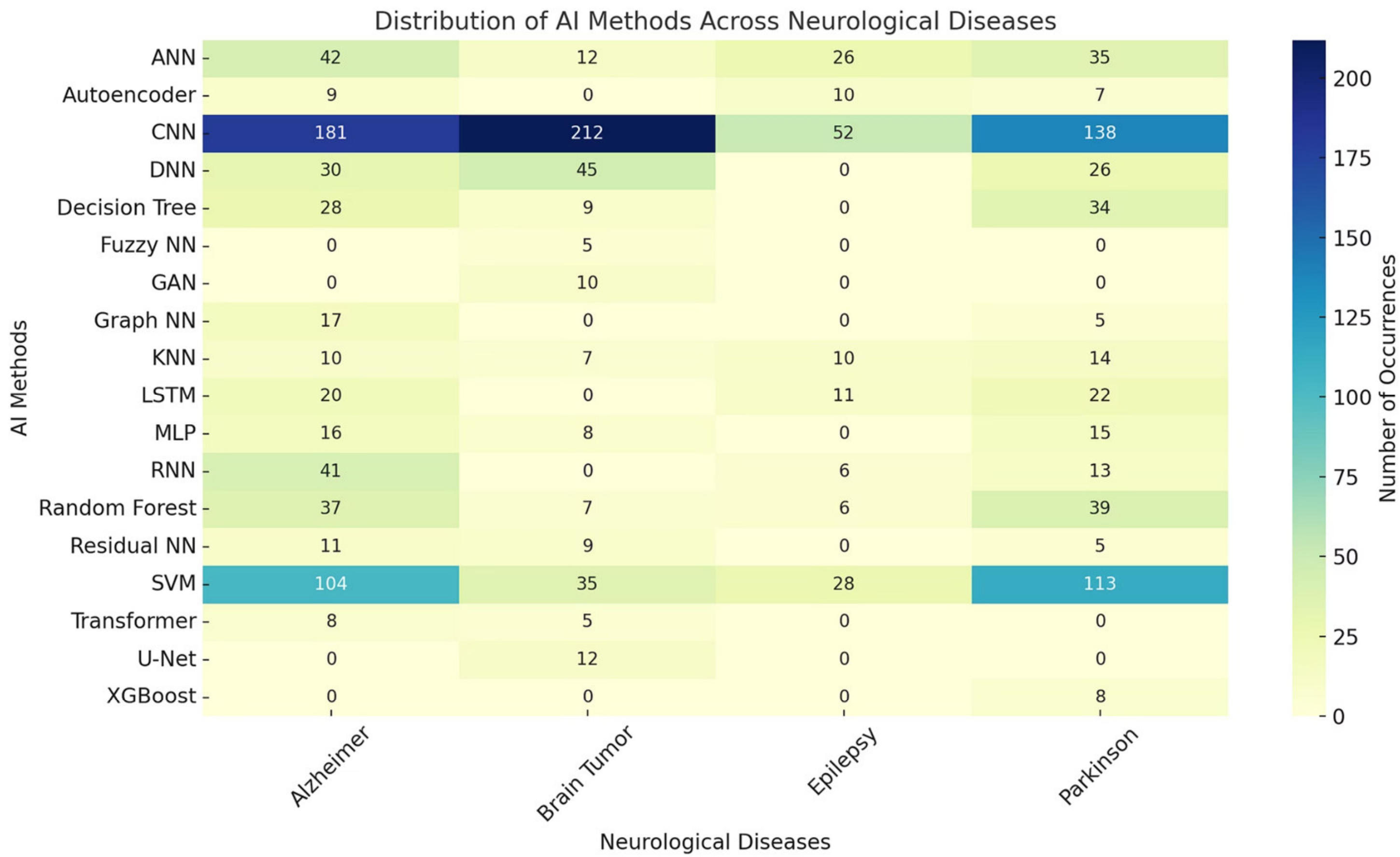
## Dominant AI Methods by Neurological Disease

Bibliometric analysis reveals distinct preferences for AI algorithms across different neurological conditions.

**CNNs: Universal Dominance**
**Convolutional Neural Networks (CNN)** are predominantly used across all disease groups, particularly in brain tumour and Alzheimer's disease studies, owing to their strength in image analysis.

**SVMs: Parkinson's Prominence**
**Support Vector Machines (SVM)** are the second most common approach, especially prominent in studies focused on Parkinson's disease.

**RNNs & LSTMs: Time-Series Specialists**
**Artificial Neural Networks (ANN)** and **Recurrent Neural Networks (RNN)** are prominent in Alzheimer's and epilepsy research.



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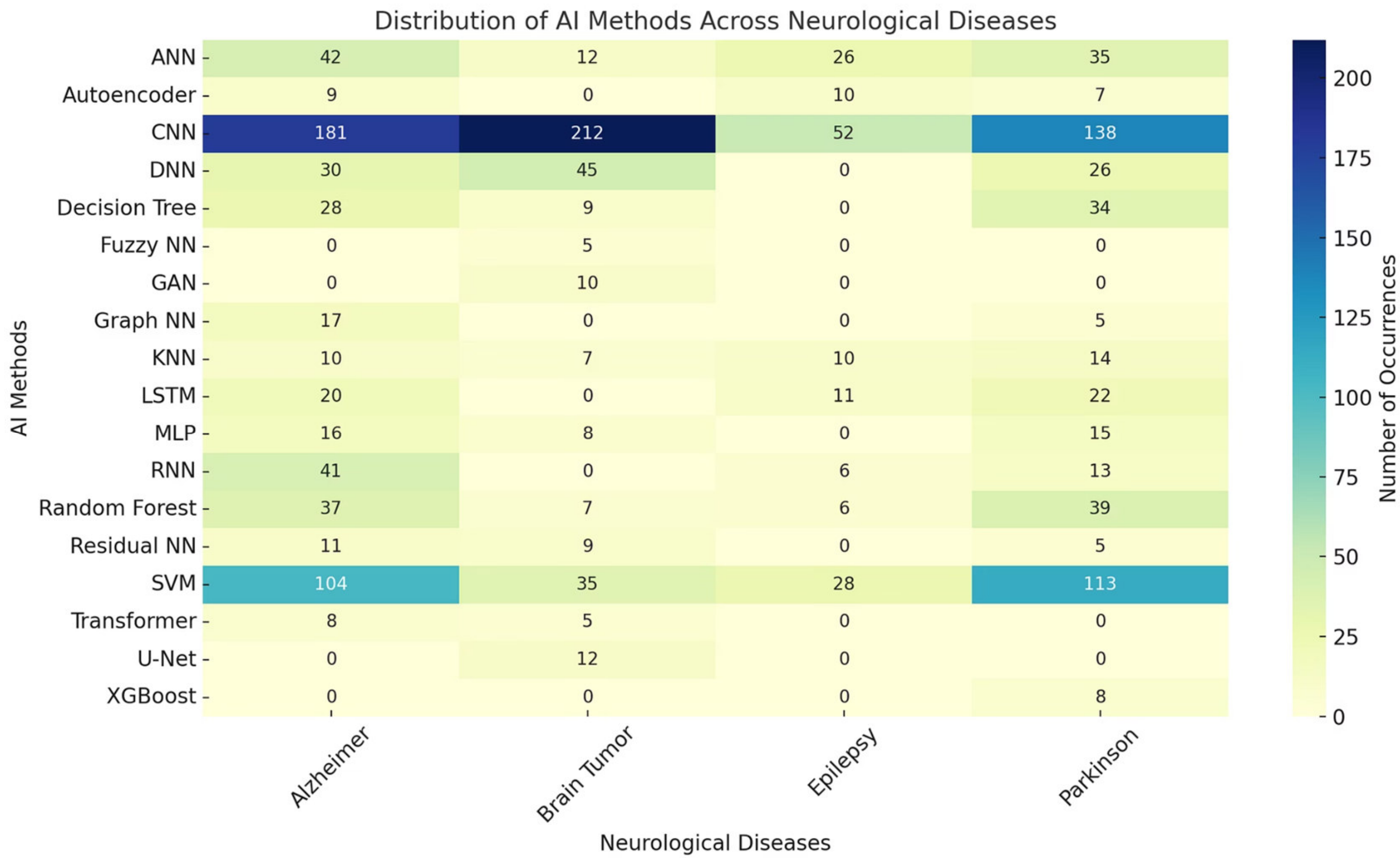
**Long Short-Term Memory (LSTM)** networks are crucial for epilepsy (EEG data) and Parkinson's (movement and voice data) due to their time-series processing capabilities.

**Emerging & Niche Methods**

**Tree-based models** (Random Forest, Decision Tree) and **Deep Neural Networks (DNN)** are widely used in Parkinson's and brain tumour studies.

**U-Net, Generative Adversarial Networks (GAN), and Fuzzy Neural Networks** are extensively used in brain tumour imaging but less so for other conditions. Newer methods like **Graph Neural Networks (GNN), Transformers, and XGBoost** are emerging but still limited.



## Trends in AI Method Utilisation (2021-2025)

The review of studies from 2021 to 2025 highlights clear trends in the application of AI methods across neurological diseases.

### CNNs Maintain Lead

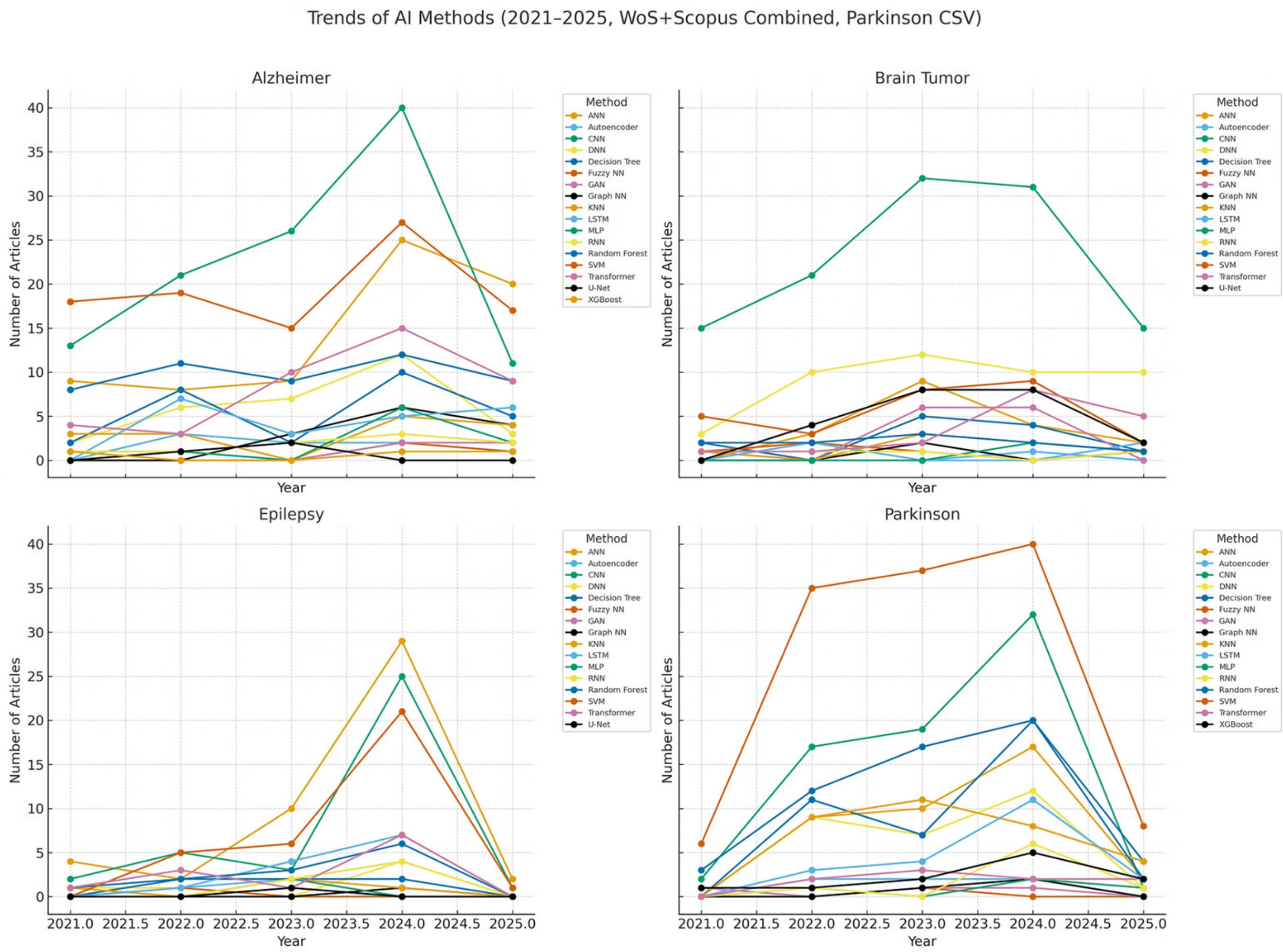
**Convolutional Neural Networks (CNNs)** continue to dominate across all neurological diseases, affirming their robustness in image-based diagnostics.

### SVMs & ANNs as Key Players

**Support Vector Machines (SVMs)** and **Artificial Neural Networks (ANNs)** remain significant, often complementing CNNs or serving as primary methods in specific contexts.

### Tree-Based Models for Specific Conditions

**Tree-based models** (e.g., Random Forest, Decision Tree) are more prevalent in brain tumour and Parkinson's disease studies, indicating their utility for structured data analysis.



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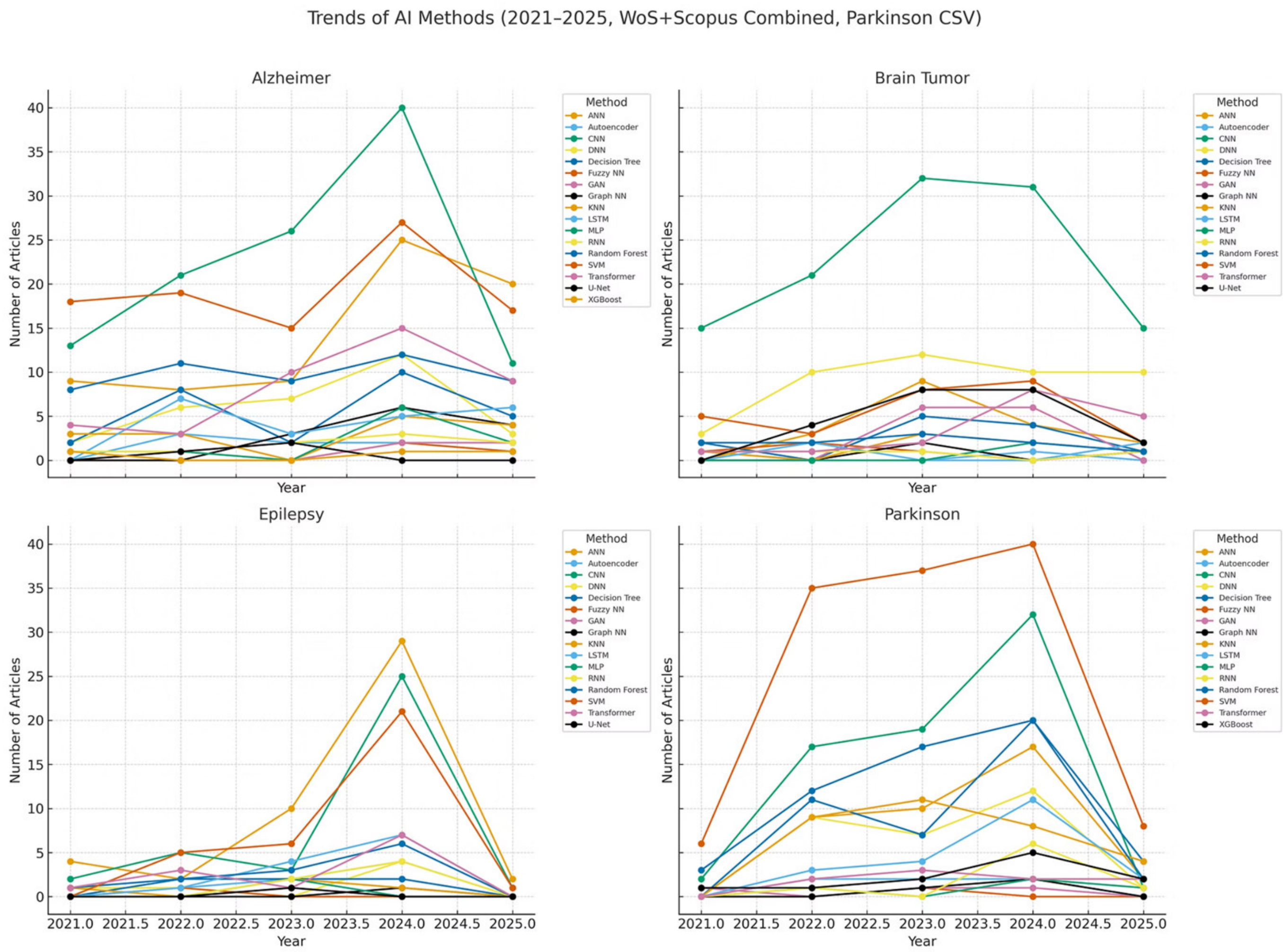
### Time-Series Methods for Dynamic Data

**Time-series methods** (RNN, LSTM) are primarily observed in epilepsy (EEG data) and Parkinson's disease (movement/voice data), reflecting their strength in processing sequential information.

### Emerging Approaches on the Rise

While still limited, emerging approaches such as **GANs, Transformers, and GNNs** have shown a notable increase in recent years, suggesting future growth and diversification in AI applications.



# Conclusion & Future Outlook

The integration of AI in neurological disease diagnosis is rapidly advancing, offering unprecedented opportunities to overcome traditional diagnostic limitations.

### AI's Critical Role

AI, particularly deep learning, is becoming indispensable for accurate and timely diagnosis of complex neurological conditions.

### Dominance of CNNs

CNNs remain the most widely adopted method, especially for image-based diagnostics in brain tumours and Alzheimer's.

### Specialised Applications

LSTMs and RNNs are crucial for time-series data in epilepsy and Parkinson's, highlighting the need for method-specific approaches.

### Future Research Directions

Further research should focus on integrating emerging AI techniques and addressing current gaps to enhance diagnostic precision and accessibility globally.

The continuous evolution of AI methods promises a future where neurological diagnoses are more efficient, less prone to error, and ultimately lead to better patient outcomes.

Thank you listening for me ☺

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