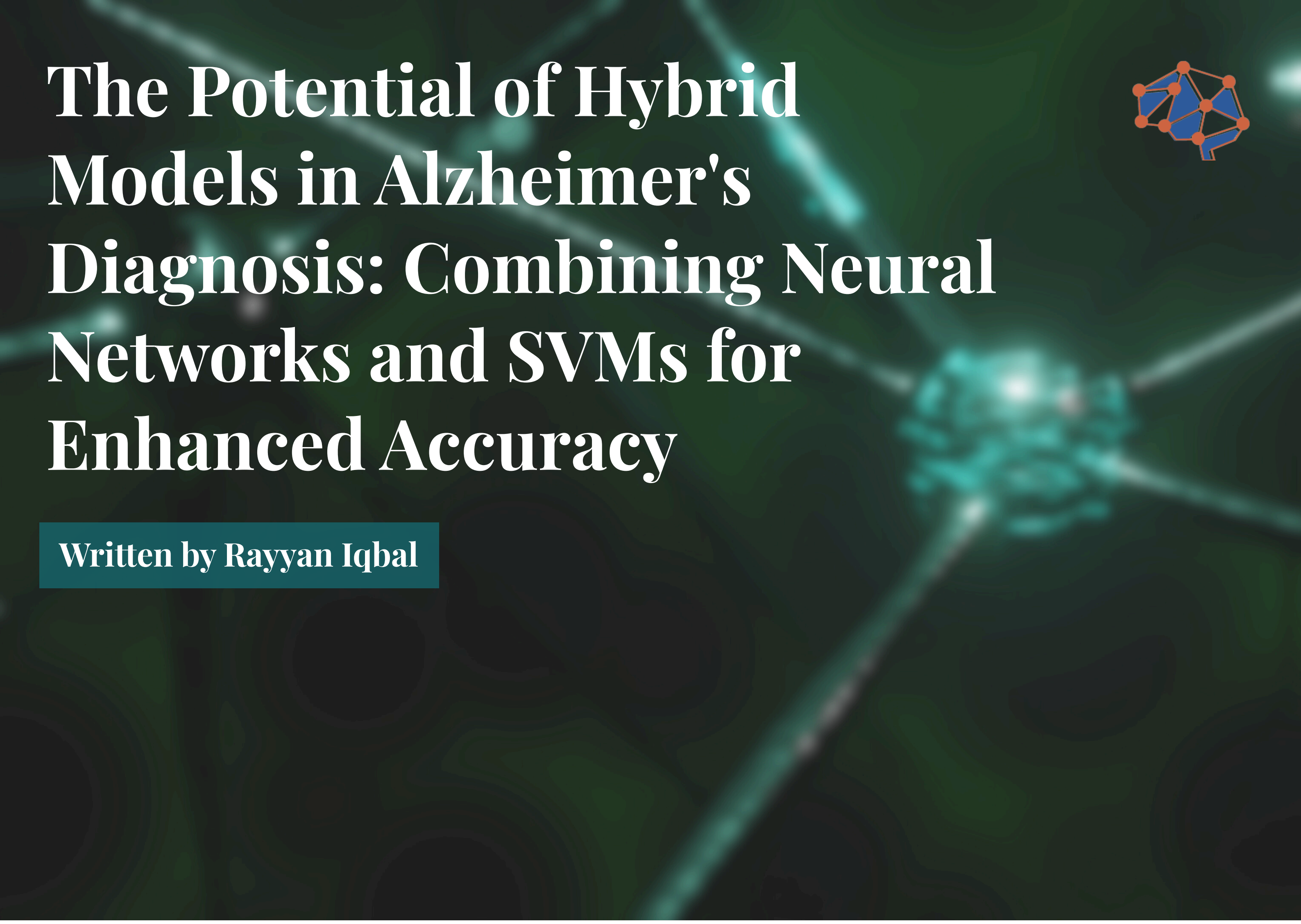
# The Potential of Hybrid Models in Alzheimer's Diagnosis: Combining Neural Networks and SVMs for Enhanced Accuracy



Written by Rayyan Iqbal

## Introduction

Alzheimer's Disease (AD) affects over 55 million people worldwide, posing a major challenge for healthcare systems as populations continue to age. As a progressive neurodegenerative disorder, AD leads to severe cognitive decline, memory loss, and a profound reduction in quality of life, ultimately resulting in death. The mortality rate for AD approaches 100%, with patients typically living only 3 to 11 years after diagnosis, underscoring the critical importance of early detection (Alzheimer's Stages: How the Disease Progresses, n.d.). Despite extensive research, early diagnosis of AD remains difficult.

The need for early detection is clear when observing cognitive tests like clock-drawing exercises. The differences between healthy individuals and those in late-stage AD are striking; however, distinguishing early-stage AD from normal aging is much harder, as seen in the clock drawings, in which there isn't as profound of a difference in the quality of the clock drawn between normal and early AD individuals (Mattson 2014). Additionally, brain degeneration progresses significantly as AD advances, as shown in the brain degeneration image (Maha 2023). While late-stage AD presents notable structural changes, the brain deterioration in early stages is minimal, making it challenging to identify AD before symptoms become severe.

Traditional diagnostic methods—including clinical assessments, cognitive tests, and neuroimaging—often struggle to detect AD at these early stages, delaying the possibility of effective interventions. Recent advancements in machine learning offer new hope. Neural networks (NNs), particularly convolutional neural networks (CNNs), excel at extracting complex patterns from large datasets, such as MRI or PET scans, allowing for a more nuanced analysis of brain images (Taherdoost 2023). Support vector machines (SVMs), powerful classification tools, complement this process by distinguishing between healthy individuals and those with various degrees of cognitive impairment (Ahmadi et al., 2024).

While each model has shown promise independently, hybrid models that combine the strengths of CNNs and SVMs could further improve diagnostic accuracy. Hybrid models leverage CNNs' ability to identify intricate patterns and SVMs' adeptness at classification, potentially making early detection achievable (Li 2023). However, research in this area is still limited, with few large-scale studies validating these methods. Before these hybrid models can be integrated into clinical practice, more robust data and validation are necessary to ensure their reliability. While the potential of these hybrid models is promising, caution is urged in their application until further research solidifies their effectiveness.

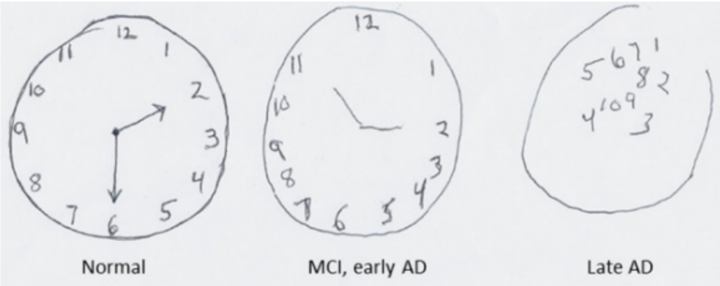



**Figure 1.** Clock drawings showing cognitive decline: Normal (accurate), Early AD (slightly distorted), Late AD (severely disorganized). (Linus Health)

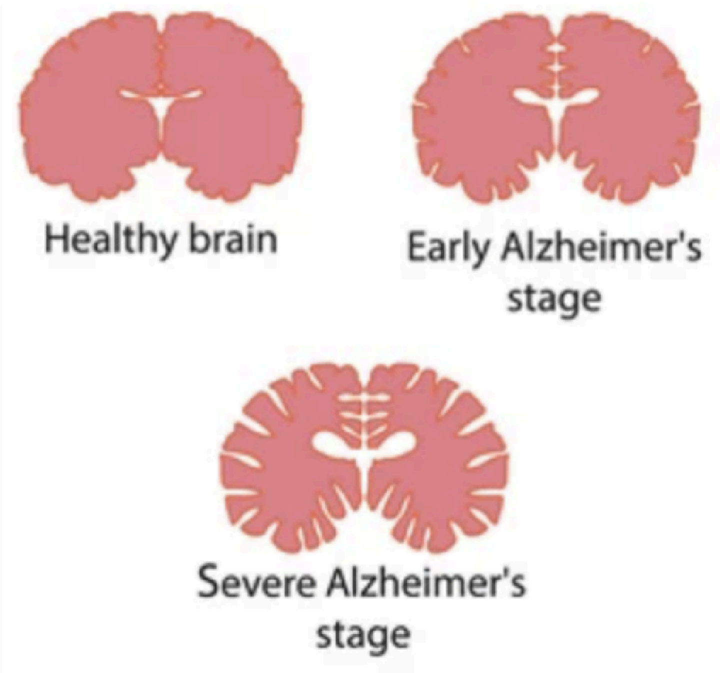



**Figure 2.** Brain atrophy progression: Healthy, Early Alzheimer's (mild shrinkage), Severe Alzheimer's (significant shrinkage). (First Choice Neurology 2019).

## Neural Networks: Identifying Early-Stage Alzheimer's in Neuroimaging

Neural networks, especially convolutional neural networks (CNNs), have proven highly effective at analyzing neuroimaging data like MRI or PET scans, which is essential for diagnosing Alzheimer's Disease in its early stages. Neural networks are inspired by the human brain's structure, consisting of interconnected layers of "neurons" that learn from data by recognizing patterns and relationships. When given input data (such as numbers, images, or text), the network adjusts the connections between these neurons to improve its understanding. This allows neural networks to perform tasks such as predicting outcomes, classifying objects, and identifying trends (Taherdoost 2023).

CNNs are a specialized type of neural network designed specifically for image data. They use a process called "convolution," where small filters scan sections of an image to identify important features like edges, shapes, or textures. Rather than analyzing the entire image at once, CNNs focus on small regions at a time, making them exceptionally good at interpreting visual information. In simple terms, while a standard neural network might act as a general "decision-maker," CNNs operate more like a team of "spotters," with each focusing on a different part of the image to capture crucial details (e.g., one "spotter" might identify the nose, another the eyes). This approach allows CNNs to excel at tasks such as recognizing objects in photos or detecting abnormalities in medical images.

CNNs can achieve remarkable accuracy in identifying early signs of Alzheimer's. In one study using a dataset of healthy individuals, those with early Alzheimer's, and those with late-stage Alzheimer's, a CNN model called ResNet-18 achieved an impressive 96.85% accuracy in distinguishing between different stages of the disease based on MRI and PET scans (Odusami et al., 2021). This performance far exceeds conventional diagnostic methods, such as physician evaluations of PET scans, which typically achieve about 85% accuracy, according to the Texas Department of State Health Services (Texas DSHS, 2021).

However, CNNs have limitations. One major drawback is their "black-box" nature, meaning they generate results without revealing how they reached those conclusions. This lack of transparency can be problematic in clinical settings, where doctors need to understand the reasoning behind a diagnosis to justify treatment decisions. Without insight into how CNNs make their determinations, it becomes challenging for physicians to fully trust and adopt these models in practice, despite their accuracy (Patil et al., 2022).

## SVMs: Precise Classification but Limited in Complex Data

While CNNs are excellent for identifying features in images, support vector machines (SVMs) are highly effective for classifying data once those features are identified. The image above illustrates how an SVM functions: two sets of data points, shown as green and red dots, represent two different classes the SVM aims to separate. The axes, labeled x1 and x2, represent a two-dimensional feature space where the data points are plotted. The blue line running diagonally across the plot is the decision boundary, which separates the two classes. This boundary isn't just any line—it is chosen to maximize the distance between itself and the nearest data points from each class, a concept known as the "margin." One of the points closest to the boundary, called a "support vector" (represented by the purple dot), plays a crucial role in defining this margin (Tan 2020).

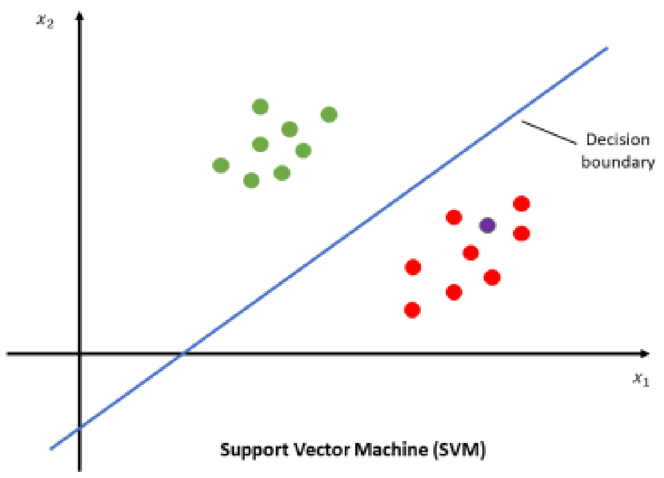



**Figure 3.** Support Vector Machine (SVM) diagram showing a decision boundary separating two classes. (Tan 2020).

SVMs have demonstrated reliable performance in classifying patients by analyzing MRI data, with their highest accuracy reaching 89%. They excel in identifying key features like gray matter volume and brain asymmetry to distinguish between control groups, early mild cognitive impairment (eMCI), late mild cognitive impairment (lMCI), and Alzheimer's disease stages. In one approach, researchers used hippocampal volume—a primary indicator of Alzheimer's—as the main feature, which contributed to the high accuracy achieved in their study (Ahmadi et al., 2024).

Despite their strengths, SVMs face challenges, particularly with high-dimensional data, where each data point has numerous characteristics or "dimensions." In such cases, it becomes harder for SVMs to identify clear patterns or find a meaningful decision boundary. Without careful feature selection and model tuning, SVMs may struggle to classify complex data accurately, leading to overfitting. Overfitting occurs when a model performs well on training data but poorly on new, unseen data, reducing its real-world effectiveness (Ameen et al., 2024).

## Hybrid Models: Combining Neural Networks and SVMs for Enhanced Accuracy

In recent years, hybrid models that combine convolutional neural networks (CNNs) and support vector machines (SVMs) have gained attention in Alzheimer's disease diagnosis, offering a more comprehensive approach to early detection and classification (Li 2023). By integrating CNNs and SVMs, these models provide a robust framework to handle the complexity of high-dimensional neuroimaging data, which is essential for identifying subtle early-stage markers of Alzheimer's.

Hybrid models leverage the unique strengths of CNNs and SVMs. CNNs are particularly skilled at extracting features from complex neuroimaging data, such as magnetic resonance imaging (MRI) and positron emission tomography (PET) scans. These models can detect early neurodegenerative changes, including hippocampal atrophy, cortical thinning, and ventricular enlargement—key biomarkers for diagnosing Alzheimer's at its early stages (Oostven 2021). However, while CNNs excel at identifying these features, they often lack the precision needed for effective classification. This is where SVMs become valuable, as they create precise boundaries that distinguish different cognitive states, such as healthy controls, patients with mild cognitive impairment (MCI), and those with Alzheimer's disease (Ahmadi et al., 2024).

A study by Al Subaie et al. demonstrated the effectiveness of a CNN-SVM hybrid model applied to neuroimaging data, showing the model's ability to distinguish between MCI patients likely to progress to Alzheimer's and those who are not. This research highlighted the advantage of combining CNNs' feature extraction capabilities with SVMs' classification strength. The hybrid model achieved a higher accuracy of 98.20%, compared to 91.70% for models relying solely on CNNs or SVMs. The model was particularly successful in detecting subtle brain changes indicative of MCI conversion, which is essential for timely intervention (Al Subaie et al., 2024).

Basheera et al. explored hybrid deep learning models using multimodal neuroimaging data, combining MRI and PET scans (Basheera et al., 2019). In this approach, the CNN component analyzed the raw imaging data to extract patterns of brain degeneration, which the SVM then classified into diagnostic categories like non-demented, MCI, and AD. This hybrid method demonstrated superior diagnostic accuracy, especially in differentiating between early MCI and advanced cognitive decline stages. The results showed that the CNN-SVM model outperformed traditional diagnostic methods and standalone machine-learning models in terms of accuracy, sensitivity, and specificity, achieving 90.47% accuracy, 86.66% recall, and 92.59% precision (Basheera et al., 2019).

Both studies emphasize the potential of hybrid models to bridge the gap between feature extraction and classification, especially when dealing with high-dimensional neuroimaging data. By allowing CNNs to identify complex biomarkers and enabling SVMs to classify these features accurately, hybrid models offer a more nuanced approach to diagnosing Alzheimer's disease. This combination captures subtle brain patterns that conventional methods might miss, which is crucial for early detection. With earlier intervention, hybrid models could lead to more accurate diagnoses and better treatment options, potentially improving patient outcomes.

## Considerations and Future Directions: Evaluating the Potential of Hybrid Models for Clinical Adoption

While hybrid models combining neural networks (NNs) and support vector machines (SVMs) show significant potential in improving the accuracy of Alzheimer's diagnosis, several challenges currently limit their adoption in clinical practice.

One major challenge is the complexity and quality of data required for these models to perform effectively. CNNs, a critical component of hybrid models, rely heavily on neuroimaging data, which is often difficult and costly to obtain at the scale needed for robust machine learning. Studies, including those focusing on multimodal approaches, have highlighted that even well-curated datasets like the Alzheimer's Disease Neuroimaging Initiative (ADNI) are often insufficiently large or diverse to ensure the generalizability of CNNs across various populations. Additionally, collecting such data is complicated by privacy concerns, which can further limit the availability of comprehensive datasets (Ismail et al., 2022).

Another significant challenge is the interpretability of hybrid models. Neural networks, especially CNNs, often function as "black boxes," producing diagnostic results without revealing how they arrived at those conclusions. This lack of transparency makes it difficult for healthcare professionals to understand and trust the model's rationale, particularly when making critical patient care decisions. While efforts like Explainable AI have aimed to make machine learning models more interpretable, the need for transparent decision-making remains a major barrier to adoption in clinical settings (Prijs et al., 2022).

In addition, hybrid models are prone to overfitting—a problem where the model performs well on training data but poorly on new, unseen data. This is especially relevant for models that incorporate both SVMs and CNNs, as SVMs can struggle with high-dimensional data without careful feature selection, and CNNs require extensive computational resources and large datasets to avoid overfitting. If not properly managed, overfitting can undermine the model's real-world effectiveness and limit its reliability in clinical settings (Ying 2019).

Overall, while hybrid models hold great promise, they are not yet ready for widespread clinical adoption. More research is needed to validate their performance across larger, more diverse datasets and to address issues related to interpretability and scalability. Addressing these challenges will be essential for realizing the full potential of hybrid models in Alzheimer's diagnosis and ensuring they can be safely and effectively integrated into everyday clinical practice (Wang et al., 2024).

## Conclusion

The integration of neural networks and support vector machines represents a promising approach to improving early Alzheimer's diagnosis. Neural networks, particularly convolutional neural networks (CNNs), excel at identifying subtle patterns in neuroimaging data, while SVMs provide precise classification capabilities. By combining these techniques in hybrid models, diagnostic accuracy can be significantly enhanced, potentially enabling earlier intervention and improved patient outcomes (Oostven et. al., 2021).

However, despite these advancements, the field remains under-researched. The studies conducted so far, while encouraging, are not yet sufficient to support the widespread adoption of hybrid models in clinical practice. More research is necessary to validate these models on larger and more diverse datasets and to address their limitations, particularly in terms of neural network interpretability and the extensive feature selection required for SVMs.

As machine learning continues to evolve, hybrid models combining neural networks and SVMs may ultimately transform Alzheimer's diagnosis, enabling more accurate and timely detection. For now, however, these methods should be approached with caution, as further rigorous and repetitive studies are needed to confirm their reliability in clinical settings. With continued research, these models could one day offer a breakthrough in diagnosing and managing Alzheimer's disease.

## References

**1.** Ahmadi, M., Javaheri, D., Khajavi, M., Danesh, K., & Hur, J. (2024). A deeply supervised adaptable neural network for diagnosis and classification of Alzheimer's severity using multitask feature extraction. PLoS ONE, 19(3), e0297996. https://doi.org/10.1371/journal.pone.0297996

**2.** Ameen, T. B., Kashif, S. N., Abbas, S. M. I., Babar, K., Ali, S. M. S., & Raheem, A. (2024). Unraveling Alzheimer's: the promise of aducanumab, lecanemab, and donanemab. The Egyptian Journal of Neurology Psychiatry and Neurosurgery, 60(1). https://doi.org/10.1186/s41983-024-00845-5

**3.** Alsubaie, M. G., Luo, S., & Shaukat, K. (2024). Alzheimer's Disease Detection Using Deep Learning on Neuroimaging: A Systematic review. Machine Learning and Knowledge Extraction, 6(1), 464–505. https://doi.org/10.3390/make6010024

**4.** Basheera, S., & Ram, M. S. S. (2019). Convolution neural network–based Alzheimer's disease classification using hybrid enhanced independent component analysis based segmented gray matter of T2 weighted magnetic resonance imaging with clinical valuation. Alzheimer's & Dementia: Translational Research & Clinical Interventions, 5(1), 974–986. https://doi.org/10.1016/j.trci.2019.10.001

**5.** Ismail, W. N., PP, F. R., & Ali, M. A. S. (2022). MULTFORAD: Multimodal MRI neuroimaging for Alzheimer's disease detection based on a 3D convolution model. Electronics, 11(23), 3893. https://doi.org/10.3390/electronics11233893

**6.** Li, M., Jiang, Y., Zhang, Y., & Zhu, H. (2023). Medical image analysis using deep learning algorithms. Frontiers in Public Health, 11, 1273253. https://doi.org/10.3389/fpubh.2023.1273253

**7.** Odusami, M., Maskeliūnas, R., Damaševičius, R., & Krilavičius, T. (2021). Analysis of Features of Alzheimer's Disease: Detection of Early Stage from Functional Brain Changes in Magnetic Resonance Images Using a Finetuned ResNet18 Network. Diagnostics, 11(6), 1071. https://doi.org/10.3390/diagnostics11061071

**8.** Patil, V., Madgi, M., & Kiran, A. (2022). Early prediction of Alzheimer's disease using convolutional neural network: a review. The Egyptian Journal of Neurology Psychiatry and Neurosurgery, 58(1). https://doi.org/10.1186/s41983-022-00571-w

**9.** Taherdoost, H. (2023). Deep Learning and Neural Networks: Decision-Making Implications. Symmetry, 15(9), 1723. https://doi.org/10.3390/sym15091723

**10.** Van Oostveen, W. M., & De Lange, E. C. M. (2021). Imaging Techniques in Alzheimer's Disease: A review of applications in early diagnosis and longitudinal monitoring. International Journal of Molecular Sciences, 22(4), 2110. https://doi.org/10.3390/ijms22042110

**11.** Wang, Y., Gao, R., Wei, T., Johnston, L., Yuan, X., Zhang, Y., & Yu, Z. (2024). Predicting long-term progression of Alzheimer's disease using a multimodal deep learning model incorporating interaction effects. Journal of Translational Medicine, 22(1). https://doi.org/10.1186/s12967-024-05025-w

**12.** Ying, X. (2019). An Overview of Overfitting and its Solutions. Journal of Physics: Conference Series, 1168, 022022. https://doi.org/10.1088/1742-6596/1168/2/022022

Images:

**1.** First Choice Neurology. (2019). June is Alzheimer's and Brain Awareness Month. *First Choice Neurology*. Retrieved February 18, 2025, from https://www.fcneurology.net/june-is-alzheimers-and-brain-awareness-month/

**2.** Linus Health. (n.d.). History of the Clock Drawing Test and the Linus Health Platform. *Linus Health*. Retrieved February 18, 2025, from https://linushealth.com/history-of-clock-drawing-test-and-dctclock

**3.** Tan, A. (2020). Support Vector Machine. *Anthony's Blogs*. Retrieved February 18, 2025, from https://anthony-tan.com/Discriminant-Functions-and-Decision-Boundary/

## About the Author

Rayyan Iqbal is a sophomore at the University of Illinois, majoring in Chemistry. He is currently conducting research in the Physical Activity and Neurocognitive Health Lab, where he studies the impact of physical behaviors—such as physical activity and sedentary time—on brain health. Beyond his research, Rayyan is actively involved in REACT, an outreach program that brings science to life for young students in the Champaign-Urbana area.