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Survey on Handwriting Analysis for Early Detection of Alzheimer

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Abstract— Alzheimer's Disease (AD), a debilitating neurodegenerative condition, progressively impairs cognitive abilities and motor coordination. Timely diagnosis is crucial for intervention, yet conventional approaches like neuroimaging and cerebrospinal fluid analysis remain costly, invasive, and often ineffective in early stages.Recent advancements highlight digital handwriting analysis as a viable, non-invasive alternative for detecting subtle cognitive deterioration linked to AD. This review systematically evaluates contemporary research on handwriting-based diagnostics, focusing on key metrics—pen pressure variability, stroke irregularities, micro-tremors, and spatiotemporal inconsistencies—that correlate with early-stage AD. We compare conventional statistical models with cutting-edge AI-driven techniques, assessing their efficacy, dataset dependencies, and feature-selection strategies. Furthermore, we identify gaps in current methodologies and suggest innovations to improve clinical adoption, such as integrating real-time digital pen data with multimodal biomarkers. By synthesizing these insights, this work serves as a roadmap for developing scalable, cost-effective tools to detect AD through handwriting anomalies.

***Index Terms*—** Alzheimer's disease, early detection, handwriting analysis, cognitive decline, digital health, pen-based monitoring, machine learning, motor function assessment, behavioral biomarkers, neurodegenerative disorders.

I. INTRODUCTION

Alzheimer's Disease (AD) is a long-term, irreversible brain disorder that mainly affects older populations. It is recognized as the leading cause of dementia worldwide, contributing to approximately 70% of diagnosed cases. AD gradually impairs memory, reasoning, behavior, and motor coordination, severely diminishing a person's ability to function independently. According to the World Health Organization (WHO), the global incidence of Alzheimer's is expected to increase substantially in the coming years, adding pressure to healthcare infrastructures and caregivers alike. One of the most significant obstacles in managing AD is its early diagnosis, which plays a crucial role in initiating treatment plans, slowing disease progression, and improving quality of life. Currently, standard diagnostic procedures for Alzheimer's involve a combination of brain imaging techniques like MRI or PET scans, spinal fluid testing, and cognitive assessments. Although these methods are generally reliable, they are often associated with high costs, limited availability, and invasive procedures—particularly unsuitable for widespread or early-stage screening.

These limitations have led researchers to investigate alternative approaches that are non-invasive, economical, and practical for early detection. One emerging field of interest is handwriting analysis, which shows potential in identifying minor motor and cognitive dysfunctions related to the initial phases of Alzheimer's.

Writing is a skill that demands fine coordination between vision, motor control, and mental processing. As these systems begin to decline, subtle but detectable alterations in handwriting can occur well before traditional symptoms are noticed. Research indicates that early-stage Alzheimer's patients often display reduced writing speed, inconsistent line pressure, tremors, and irregular spacing between letters and words. With the help of digital tools such as smart pens or tablets, these deviations can be accurately recorded and measured, providing a reliable and non-invasive means of early diagnosis.

The evolution of artificial intelligence and signal processing has paved the way for intelligent handwriting recognition systems that can identify these abnormalities with high precision. Techniques such as pattern recognition, supervised classification, and feature extraction have been applied to differentiate normal aging from pathological decline. Both static samples, like signatures, and dynamic data from stylus-enabled devices are being used in current research to detect abnormalities invisible to the human eye.

This paper offers a thorough review of research efforts centered on handwriting-based Alzheimer's detection. It discusses commonly used features, classification models, dataset types, and evaluation criteria. By compiling and comparing prior work, this survey aims to establish a foundational understanding of the field, recognize ongoing challenges, and highlight potential directions for future research. The goal is to contribute toward the creation of accessible, reliable tools for early and scalable Alzheimer's screening.

Furthermore, the integration of handwriting analysis into existing digital health systems opens up opportunities for community-level screening and long-term cognitive monitoring. With the widespread use of smartphones, tablets, and styluses, data can now be collected seamlessly in everyday environments. This remote and non-intrusive approach reduces the clinical burden and increases diagnostic reach, especially in rural or under-resourced regions. As digital technologies continue to evolve, handwriting analysis emerges as a timely and promising technique to support the early identification of Alzheimer's Disease in real-world settings.

II. Literature Survey

In this section, various authors have presented various face recognition and detection techniques.

Belic et al. [1] conducted a comprehensive review on the application of artificial intelligence (AI) in the diagnosis and assessment of Parkinson's Disease (PD), highlighting its relevance in neurodegenerative disease research. Although the paper primarily focuses on PD, the methodologies discussed are highly transferable to Alzheimer's Disease, especially in the context of early detection using machine learning. The review emphasizes how AI models can assist in analyzing complex clinical data such as motor patterns, voice recordings, and handwriting dynamics to detect disease symptoms that may not be immediately obvious to clinicians. The authors evaluated several machine learning algorithms, including neural networks, support vector machines, and fuzzy logic systems, illustrating their utility in distinguishing between healthy individuals and those showing early signs of neurodegeneration. The study also sheds light on the challenges of integrating AI into clinical workflows, such as data standardization, interpretability of models, and the need for large, labeled datasets. These insights are directly relevant to handwriting-based analysis for Alzheimer's, where similar machine learning strategies can be applied to detect subtle cognitive and motor impairments from writing samples. This review establishes a solid foundation for understanding how AI tools can support the early diagnosis of neurological disorders and reinforces the importance of digital biomarker research in cognitive healthcare.

Scott, Carter, and Coiera [2] proposed a structured clinician-oriented checklist designed to evaluate the appropriateness and reliability of machine learning (ML) applications in healthcare settings. The checklist covers essential factors such as clinical relevance, data quality, algorithm transparency, validation protocols, and integration feasibility. Although their work is not focused specifically on Alzheimer's or handwriting analysis, it provides a vital framework for assessing any ML-based diagnostic tool, including those used for early detection of neurodegenerative disorders. The authors emphasized that successful deployment of ML in healthcare requires not only technical accuracy but also alignment with clinical workflows and ethical standards. In the context of handwriting analysis for Alzheimer's detection, this study underscores the importance of model explainability, data representativeness, and clinician involvement in system evaluation. Their checklist can serve as a guideline for evaluating the suitability of handwriting-based diagnostic models, ensuring that the technology developed is not only accurate but also clinically viable, reproducible, and ethically sound.

In [3], Precup et al. explored the use of evolving fuzzy logic models for the control of prosthetic hands using myoelectric signals. While the study is rooted in the domain of assistive robotics, the methodology demonstrates the potential of adaptive intelligent systems to interpret complex biosignals with high precision. The authors employed fuzzy inference

systems that evolve in response to changing input patterns, making them suitable for modeling non-linear, variable human input—such as that found in neuromuscular impairments. This
approach highlights the adaptability of soft computing methods for real-time biomedical applications. For Alzheimer's handwriting analysis, the concept of using flexible and evolving models can be highly beneficial, as patients' writing characteristics may change subtly over time or vary significantly between individuals. The study's emphasis on myoelectric-based control parallels the cognitive-motor dynamics present in handwriting tasks, suggesting that similar adaptive modeling techniques could enhance the accuracy of handwriting-based diagnostics for neurodegenerative diseases.

Vessio [4] offers a detailed survey centered on the application of dynamic handwriting analysis in evaluating neurodegenerative conditions. Unlike static handwriting assessments, this work emphasizes the diagnostic potential of real-time handwriting metrics, such as stroke speed, writing pressure, motion acceleration, and in-air pen movements. These dynamic features provide deeper insights into neuromuscular coordination, which tends to decline in the early stages of diseases like Alzheimer's and Parkinson's. The review also examines a variety of machine learning models and feature extraction methods—including neural networks, decision trees, and support vector machines—used to process these inputs. In addition to exploring benefits, the paper highlights practical challenges such as inconsistencies in handwriting data and device calibration issues. Overall, the study makes a strong case for digital handwriting analysis as a non-invasive, accessible tool for early detection of cognitive impairment.

De Stefano et al. [5] provide a broad analysis of handwriting-based techniques for diagnosing neurodegenerative disorders, particularly Alzheimer's and Parkinson's. Their review covers both static features (like letter shape and spacing) and dynamic metrics (such as writing speed and stroke duration) that may correlate with cognitive and motor decline. They categorize the literature based on feature types and modeling strategies, including deep learning, hybrid models, and statistical classifiers. Notably, the authors address existing limitations in the field, such as the variation in individual handwriting styles and the lack of standardized testing tasks. The review emphasizes that, despite these obstacles, handwriting analysis holds significant promise as a low-cost, non-invasive diagnostic method—especially when combined with machine learning techniques to enhance predictive performance. This work offers a solid theoretical base for further research and development of early-stage diagnostic tools using handwriting data.

In their study, Singh and Yadav [6] explore how various neurodegenerative diseases manifest in handwriting, providing insights valuable to both clinical diagnosis and forensic analysis. They identify common handwriting changes in affected individuals, including abnormal letter spacing, misalignment, tremors, and overall degradation in writing

quality. These features often emerge early and can serve as visible indicators of underlying neurological deterioration.
The authors argue that handwriting can bridge the gap between behavioral symptoms and deeper neurological pathology, offering a useful and explainable tool for screening. While the paper is rooted in forensic science, its findings align with current trends in using handwriting as a behavioral biomarker for Alzheimer's diagnosis, particularly when combined with machine learning approaches that detect motor and cognitive irregularities embedded in writing patterns.

A notable contribution to the field is provided by Impedovo et al. [7], where the authors introduce a structured protocol centered on handwriting analysis for the assessment of neurodegenerative dementia. This protocol comprises a series of standardized writing tasks specifically designed to capture both motor and cognitive functions through features like pen pressure fluctuations, stroke continuity, and in-air movement patterns. These handwriting features are examined using machine learning techniques to distinguish between healthy individuals and those in the early stages of cognitive decline. The approach is significant in that it evaluates both the physical and neurological aspects of handwriting behavior, offering a more integrated perspective on early disease detection. Their experimental findings demonstrate the effectiveness of the method in terms of classification accuracy, positioning it as a practical, scalable, and non-invasive approach to Alzheimer's screening. This work lays a strong foundation for the application of AI in behavioral health diagnostics.

Impedovo, Pirlo, and Vessio [8] investigate how dynamic handwriting analysis can aid in the early identification of Parkinson's disease, offering insights that are equally relevant to Alzheimer's research. The study concentrates on extracting handwriting features that evolve over time, including stroke speed, writing pressure, and fluidity, which are often affected by neuromotor disorders. Through the use of digitizing tablets and machine learning algorithms, the authors demonstrate how minor variations in handwriting can be used to detect early signs of motor impairment. Although their primary focus is Parkinson's, the underlying concept—monitoring fine motor control through writing—is highly applicable to Alzheimer's, where similar impairments occur. Their work underscores the potential of handwriting dynamics as a behavioral biomarker for neurodegenerative diseases, capable of capturing early-stage changes that might be overlooked in conventional assessments.

Cavallo et al. [9] explore the use of machine learning for pre-clinical motor assessment in Parkinson's disease, focusing specifically on upper limb movements. The study uses sensor-based systems to record fine motor activity and applies classification algorithms to detect early motor irregularities before visible symptoms appear. While Parkinson's is the main subject of this research, the methodology is highly relevant to Alzheimer's detection, particularly due to its emphasis on subtle neuromotor disruptions. Since handwriting involves similar fine motor coordination, analyzing such tasks can reveal early cognitive decline. The integration of real-time motion data with intelligent analysis models shows promise in detecting neurological deterioration at a stage when traditional diagnostic tools may not yet be effective. This approach highlights the value of motion-based assessments, including handwriting, in developing early and accessible screening systems for neurodegenerative conditions.

Myszczynska et al. [10] present an extensive review of machine learning applications in the diagnosis and treatment of various neurodegenerative conditions, including Alzheimer's, Parkinson's disease, and amyotrophic lateral sclerosis (ALS). The paper explores multiple ML approaches—such as supervised learning models, deep neural networks, and reinforcement learning techniques—demonstrating their capability to process complex medical datasets, including neuroimaging, genetic markers, and behavioral signals. A key strength of this review lies in its emphasis on the ability of machine learning algorithms to identify disease-specific patterns well before the emergence of clinical symptoms. Although handwriting analysis is not directly addressed, the broader insights into behavioral data modeling offer valuable support for handwriting-based diagnostics. The study further discusses practical challenges like inconsistent data formats, lack of standardized protocols, and the difficulty of interpreting black-box models—factors that are equally significant in the development of AI-driven handwriting screening tools for Alzheimer's disease.

Prasad, Reddy, and Reddy [11] conducted a focused investigation into the use of machine learning for handwriting analysis aimed at early Alzheimer's detection. Their work involves the collection of handwriting samples, from which both spatial and temporal characteristics are extracted—such as pen pressure consistency, stroke speed, letter spacing, and writing stability. These features are then fed into machine learning classifiers like Support Vector Machines (SVM) and Random Forests to categorize individuals as either healthy or showing early signs of cognitive decline. The study reports high accuracy in classification, highlighting the effectiveness of handwriting as a reliable, non-invasive indicator of Alzheimer's. The authors also stress the importance of early screening in reducing long-term health burdens and enabling timely intervention. Their findings form a foundational basis for further exploration of AI applications in behavioral biometrics for neurodegenerative disease detection.

Li, Zhang, and Liu [12] propose an innovative handwriting-based diagnostic model tailored to detect early Alzheimer's symptoms. Their approach combines deep learning techniques with detailed handwriting feature analysis to capture fine-grained neuromotor variations. The framework evaluates spatial-temporal elements of writing, including inter-letter spacing, pen-lift timing, stroke fluidity, and pressure changes throughout a written sequence. They introduce a hybrid neural network that leverages both convolutional and recurrent layers to interpret the spatial and sequential patterns present in handwriting. Their experimental results demonstrate strong diagnostic accuracy, with high sensitivity and specificity in distinguishing between Alzheimer's-affected and healthy individuals. An important aspect of this study is the focus on model explainability, ensuring that the system's predictions are transparent and interpretable for clinical use. The research effectively illustrates how AI-integrated handwriting analysis can serve as a scalable and accessible method for early detection of Alzheimer's disease.

Cilia et al. [13] explore an innovative approach to Alzheimer's disease detection by transforming online handwriting data into synthetic image representations, which are then analyzed using deep transfer learning techniques. The study utilizes a framework that converts temporal handwriting signals—captured from digital pens or tablets—into visual images that preserve dynamic characteristics such as stroke pressure, direction, and timing. These synthetic images are processed through pre-trained convolutional neural networks (CNNs), enabling the model to leverage learned features from large-scale image datasets and adapt them to the task of cognitive decline classification. The authors report promising accuracy levels, indicating the viability of combining handwriting dynamics with deep image-based representations. This approach offers a novel angle in Alzheimer's diagnostics, merging behavioral signal processing with advanced computer vision techniques. Moreover, the methodology highlights the flexibility of transfer learning in domains with limited labeled data, a common challenge in clinical research.

Dao, El-Yacoubi, and Rigaud [14] propose a deep learning-based system for detecting Alzheimer's disease through the analysis of online handwriting using a one-dimensional convolutional neural network (1D-CNN). The study focuses on capturing time-series handwriting data, such as pen pressure, writing speed, and stroke trajectories, which are fed directly into the 1D-CNN model for classification. Unlike traditional two-dimensional image approaches, the use of 1D convolution allows the model to preserve the temporal structure and sequential nature of handwriting signals, which are crucial for identifying neuromotor irregularities linked to cognitive decline. Their experimental results demonstrate strong performance in distinguishing between Alzheimer's patients and healthy individuals. This research highlights the effectiveness of lightweight, end-to-end deep learning models in behavioral biometrics and showcases how raw handwriting signals—without complex preprocessing—can still yield reliable diagnostic insights. The approach also contributes to developing more efficient and scalable screening tools for early Alzheimer's detection in real-world settings.

Mitra and Rehman [15] present a comprehensive study on the application of machine learning to handwriting analysis for the early detection of Alzheimer's disease. Their framework involves collecting a diverse set of handwritten samples and extracting both static and dynamic features, including character shape, stroke direction, pen pressure, and writing rhythm. The extracted features are analyzed using a range of supervised
learning algorithms such as decision trees, support vector machines, and ensemble classifiers. The study also compares
the performance of different models based on metrics like accuracy, precision, and recall. One notable aspect of their
work is the emphasis on feature selection techniques to enhance model interpretability and reduce computational

complexity.The results confirm that handwriting can serve as a practical and effective behavioral biomarker when processed using well-tuned machine learning pipelines. The paper reinforces the growing evidence that intelligent handwriting analysis can assist in identifying Alzheimer's at an early stage, potentially before clinical symptoms become fully observable.

Khan, Nasution, and Subramaniam [16] investigate the potential of offline handwriting image analysis for predicting Alzheimer's disease using deep learning techniques. In their study, handwritten text samples are digitized and processed as static images, allowing the extraction of visual features such as character distortion, spacing irregularities, and stroke fragmentation—patterns often observed in individuals with cognitive decline. These image-based inputs are fed into a convolutional neural network (CNN) designed to classify subjects based on the presence or absence of Alzheimer's-related writing anomalies. The authors demonstrate that even offline handwriting, without dynamic temporal data, can yield meaningful insights when paired with powerful deep learning models. Their results suggest that visual handwriting deterioration—captured in scanned documents or written forms—can act as a predictive marker of neurological disorders. This approach expands the accessibility of handwriting-based screening by eliminating the need for specialized hardware, making it applicable in both clinical and community settings.

Subha, Nayana, and Selvadass [17] present a hybrid machine learning approach that leverages Particle Swarm Optimization (PSO) to enhance the accuracy of Alzheimer's disease detection using handwriting data. The study integrates PSO with conventional classifiers to optimize feature selection and model parameters, resulting in improved classification performance. Handwriting features analyzed in this study include curvature irregularities, stroke velocity, and spacing distortions—attributes commonly linked to cognitive and motor decline in Alzheimer's patients. The hybrid model is trained and validated on handwriting datasets to distinguish between healthy individuals and those exhibiting early signs of Alzheimer's. The authors report a significant increase in accuracy compared to standard machine learning models without optimization. This work demonstrates the effectiveness of combining bio-inspired optimization algorithms with traditional ML methods in the context of behavioral biometrics, offering a promising solution for early, non-invasive Alzheimer's screening.**SUMMARY**

Over the past decade, there has been growing interest in the use of artificial intelligence (AI) and behavioral biometrics to develop non-invasive tools for the early detection of neurodegenerative diseases. Among these, handwriting analysis has emerged as a promising avenue due to its unique combination of cognitive and motor demands. Research suggests that alterations in handwriting—often unnoticed in day-to-day life—may reveal underlying neurodegenerative changes, particularly in the early stages of Alzheimer's disease (AD). When analyzed through machine learning (ML) and deep learning frameworks, these subtle variations in stroke dynamics, pressure control, and spatial arrangement can provide diagnostic cues that are otherwise difficult to detect using traditional screening methods.

The literature presents two main branches of relevant research: studies that explore general AI applications in neurological diagnostics, and those that directly investigate handwriting as a diagnostic modality. Early foundational work by Belic et al. [1] provides a comprehensive overview of AI in Parkinson's Disease (PD) diagnosis. Although PD was the focal point, their examination of motor behavior analysis through machine learning laid essential groundwork for its application to Alzheimer's-related motor decline, particularly in handwriting. Scott et al. [2], meanwhile, shift the focus to the evaluation of AI models in clinical environments, offering a structured checklist that addresses algorithm transparency, clinical relevance, and validation. These considerations are vital for deploying handwriting-based systems in real-world healthcare scenarios. Another foundational study by Precup et al. [3] applies fuzzy logic to prosthetic hand control using myoelectric signals, demonstrating how adaptive algorithms can model human motor variation—a principle that directly supports the dynamic nature of handwriting analysis in neurodegenerative contexts.

More directly aligned with handwriting-based diagnosis, several studies have examined both the theoretical basis and practical application of handwriting as a cognitive and neuromotor biomarker. Vessio [4] highlights the diagnostic potential of dynamic handwriting analysis, focusing on time-dependent features like pen pressure, velocity, and in-air movement. These dynamic traits, when captured with high-resolution devices, offer deep insight into the motor planning deficits associated with Alzheimer's. De Stefano et al. [5] complement this by reviewing both static and dynamic handwriting features and categorizing various machine learning models used for classification. Singh and Yadav [6] offer a unique forensic perspective, discussing how handwriting can visually signal cognitive impairment. Although their study is not ML-focused, it affirms handwriting's potential as a window into neurological health.

Structured assessment protocols represent a key advancement in this field. Impedovo et al. [7] propose a standardized set of handwriting tasks that target specific motor-cognitive traits, aiming to improve consistency in data collection and analysis. In a related work [8], they apply dynamic handwriting analysis to early Parkinson's detection, emphasizing real-time stroke monitoring—an approach equally applicable to Alzheimer's.

Cavallo et al. [9] introduce another dimension by using sensor data from upper limb motion to assess early-stage Parkinson's, reinforcing the role of fine motor activities, including handwriting, as rich sources of diagnostic information. Though

these studies focus on Parkinson's, the methodologies for capturing neuromotor function are transferable to Alzheimer's assessment, particularly where writing difficulties are concerned.

Recent research has narrowed its scope to Alzheimer's detection using handwriting, exploring both traditional ML and advanced deep learning architectures. Myszczynska et al. [10] conduct a broad review of machine learning across neurodegenerative diseases and emphasize the value of behavioral data such as handwriting. Their work underscores the importance of integrating explainable AI models into healthcare. Prasad et al. [11] contribute a practical framework using spatial and temporal handwriting features, such as pen pressure, stroke speed, and writing regularity, with conventional classifiers like Support Vector Machines (SVM) and Random Forests. Li et al. [12] push the frontier further by implementing a deep learning hybrid architecture that combines convolutional and recurrent neural networks. This enables the model to interpret both the spatial patterns and temporal sequences within handwriting, leading to high diagnostic sensitivity and specificity.

Newer methodologies have taken creative directions by transforming handwriting data into novel representations for learning. Cilia et al. [13] convert online handwriting into synthetic images and process them with deep transfer learning techniques. This cross-domain application allows pretrained image recognition models to extract meaningful features from visual representations of handwriting motion, improving detection performance even with smaller datasets. Dao et al. [14] use a 1D convolutional neural network to process raw sequential handwriting data, preserving its temporal structure and enabling accurate classification without complex preprocessing. Their work supports a shift toward lightweight, real-time handwriting diagnostic systems suitable for use in digital devices.

In terms of optimization and feature refinement, Mitra and Rehman [15] develop an ML framework that emphasizes feature selection and interpretability. Their study compares different classification algorithms and validates the role of stroke geometry, pressure modulation, and spatial alignment as strong predictors of early Alzheimer's. Khan et al. [16] investigate static handwriting images and apply convolutional neural networks for analysis, proving that even offline handwriting (e.g., scanned forms) contains valuable diagnostic signals. This widens the applicability of handwriting analysis to settings where digital input devices may not be available. Subha et al. [17] introduce a novel hybrid approach by integrating Particle Swarm Optimization (PSO) with ML classifiers, improving model performance and reducing computational overhead. Their system demonstrates how nature-inspired algorithms can be combined with behavioral biometrics to enhance Alzheimer's detection accuracy.

Taken together, these studies present a compelling case for handwriting analysis as a viable, scalable, and clinically relevant tool for early Alzheimer's screening. From static handwriting forms to real-time dynamic data captured by smart pens and tablets, handwriting offers a unique lens into the brain's neuromotor and cognitive systems. The convergence of handwriting-based input with machine learning opens opportunities for real-world deployment in clinics, remote monitoring platforms, and community health programs. Importantly, these techniques are non-invasive, easy to implement, and well-suited for continuous tracking of cognitive health over time.

As a behavioral biomarker, handwriting captures both deliberate and unconscious elements of brain function, making it highly sensitive to early changes caused by neurodegeneration. The transition from traditional cognitive testing to AI-enabled handwriting analysis represents not just a technological evolution, but a paradigm shift in how Alzheimer's and similar diseases might be detected and monitored in the near future. However, challenges remain, including dataset standardization, cross-linguistic variability, ethical considerations, and model interpretability. Addressing these limitations will be essential for moving from academic validation to clinical adoption.

In conclusion, the reviewed literature strongly supports the integration of machine learning with handwriting analysis as a transformative tool for early Alzheimer's detection. The diversity of approaches—from classical ML to deep learning, and from raw signal processing to optimized hybrid models—illustrates the richness of this emerging field. With continued advancements and multidisciplinary collaboration, handwriting-based diagnostic systems could soon become an integral part of routine cognitive assessments, offering earlier, faster, and more accessible Alzheimer's detection worldwide.

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