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DxDetekt: A Dyslexia Detection Method from Handwriting using Ensemble Method

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***Abstract*—Millions of people throughout the world suffer from dyslexia, which is a learning impairment. Early detection of dyslexia is crucial for effective intervention, but traditional dyslexia screening methods such as psychometric tests and DSM - V criteria, have limitations in detecting the disorder in its early stages when symptoms may not be severe enough to be detected and also they are time-consuming and require specialized expertise. This can lead to problems that negatively affect academic and social functioning. In this context, the development of novel techniques for dyslexia identification is critical for early intervention and effective support. DxDetekt aims to explore the potential of deep learning techniques for dyslexia detection using handwriting analysis. Specifically, DxDetekt investigates the effectiveness of an ensemble of Convolutional Neural Network (CNN) models and a CNN - Long Short - Term Memory (CNN - LSTM) model for dyslexia identification, which combines the predictions of multiple models to improve accuracy and reliability. The system inputs handwriting image samples and produces a dyslexia score as output. The CNN model extracts image features and is trained to classify the input sample as dyslexic or non-dyslexic. The CNN-LSTM model processes the input image sequence and captures the temporal dependencies in the handwriting sequence. The output of both models is combined using an ensemble approach to improve the accuracy of dyslexia detection. DxDetekt was implemented and evaluated using a dataset of handwriting samples from dyslexic and non–dyslexic individuals. The proposed approach has the potential to overcome the limitations of traditional diagnostic methods and provide a more accurate and effective tool for identifying dyslexia in its early stages.**

***Index Terms*— Dyslexia, CNN, CNN-LSTM, Ensemble methods, Handwriting, Reading Disability, SpLD, Learning Disability.**

I. Introduction

Despite having normal intelligence and education, dyslexia is a learning disorder that impairs a person's ability to read, write, and spell. It can be identified using psychometric testing and DSM-V criteria and is brought on by variations in how the brain perceives written and verbal language. Dyslexia affects an estimated 10-20 percent of the population, making it one of the most common learning disorders.

The exact cause of dyslexia is still not fully understood, but it is believed to be related to differences in the way the brain processes language. Researchers have identified several areas of the brain that are involved in reading and have found differences in brain activation patterns between individuals with and without dyslexia.

Dyslexia can vary in severity, and individuals with the disorder may experience different types of difficulties

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with reading and writing. Some may struggle with decoding (matching sounds to letters) and fluency (reading quickly and accurately), while others may have difficulty with comprehension or written expression. Imagine trying to read a book, but the words keep jumping around on the page, refusing to stay still. Or trying to write a simple sentence, only to find that the letters in the mind refuse to form into words on paper. For individuals with dyslexia, these struggles are all too real. Dyslexia can be a frustrating and isolating experience, leaving individuals feeling as though they are struggling to keep up with their peers. Yet, despite these challenges, individuals with dyslexia have the potential to achieve great things. In fact, some of the most successful and creative minds in history have been dyslexic. These individuals have had to find unique ways of processing information and expressing themselves, leading them to develop unconventional but highly effective methods of learning and communicating.

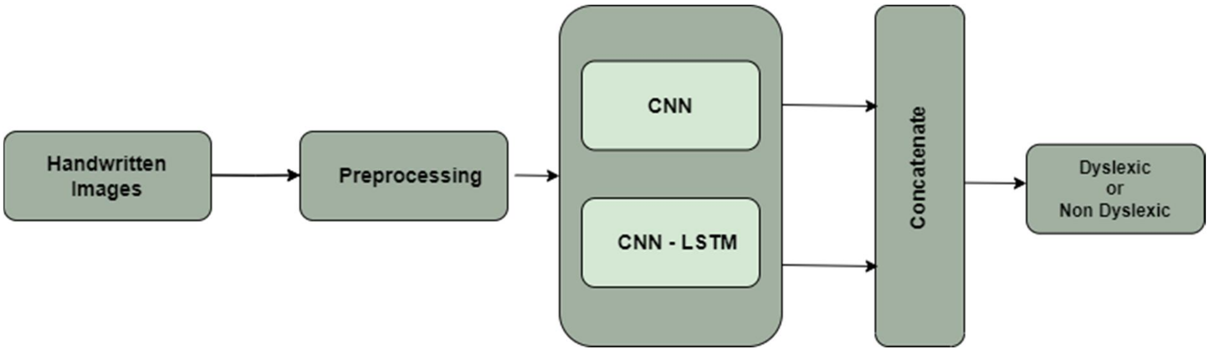

Figure 1: Architecture of DxDetekt

By recognizing dyslexia as a neurological difference rather than a deficit, we can help individuals with the disorder to embrace their strengths and overcome their challenges. With early intervention and support, individuals with dyslexia can develop the skills and confidence needed to achieve their full potential. Psychometric tests and DSM-V criteria have been the traditional methods for identifying dyslexia. However, these techniques have limitations, particularly in the early stages of dyslexia, where the symptoms may not be severe enough to be detected through these methods. While psychometric tests and DSM-V criteria provide valuable information about dyslexia, they may not capture the full extent of the disorder. In many cases, children with dyslexia may not exhibit clear signs of the condition until they start to learn how to read and write. This delay in diagnosis can lead to significant problems, including a lack of appropriate intervention and support, and can result in a negative impact on academic and social functioning.

To overcome these limitations, there has been a growing interest in developing alternative methods for identifying dyslexia. These methods leverage advances in technology and machine learning to provide early detection and intervention for individuals with dyslexia. One promising approach is the use of handwriting analysis, which has shown promise in detecting dyslexia in its early stages. DxDetekt explores the potential of deep learning techniques for dyslexia detection using handwriting analysis. In recent years, researchers have developed machine learning algorithms [1] [2] that can analyze patterns in brain scans, eye-tracking data, and other physiological measures to detect dyslexia. CNNs have been widely used for image classification tasks, and have been applied to dyslexia detection using handwriting images. However, handwriting samples also contain temporal dependencies that reflect the writing process, such as the order of strokes and the timing between them. LSTM networks have been shown to capture such temporal dependencies effectively, and have been applied to handwriting recognition tasks.

DxDetekt is an automated dyslexia detection system based on an ensemble of CNN models and a CNN-LSTM model. The system takes a handwriting image sample as input and produces a Dyslexia score as output. The CNN model extracts image features and is trained to classify the input sample as dyslexic or non-dyslexic. The CNN-LSTM model [3] processes the input image sequence and captures the temporal dependencies in the handwriting sequence. The output of both models is combined using an ensemble approach to improve the accuracy of dyslexia detection as shown in Figure 1.

DxDetekt is implemented and detected using a dataset of handwriting samples from dyslexic and non-dyslexic individuals The ensemble model achieved high accuracy, sensitivity, and specificity in detecting dyslexia from handwriting samples. DxDetekt can be an automated dyslexia detection system to facilitate early detection and effective intervention for individuals with dyslexia, especially in resource-limited settings where traditional screening methods may not be readily available. Additionally, the model had an overall ensemble accuracy of 90 percent.

II. RELATED WORKS

In recent years, there have been many studies focused on developing and evaluating automated dyslexia detection methods using machine learning and other computational techniques. Here are some related works on dyslexia detection.

A study compared the effectiveness of computerized and manual tests [4] for detecting dyslexia in young children, finding that the automated evaluation was faster and more accurate, and consistent than the manual assessment.

In [5], a methodical approach for detecting dyslexia .in early childhood is proposed. This method makes use of Artificial Neural Networks (ANN). The conventional methods for diagnosing dyslexia are time-consuming and lack a standardized methodology. The ANN model aims to improve the identification process accuracy and performance. It marks one of the earliest efforts to use ANN to recognize dyslexic students. It is difficult to understand how ANNs work because of their complex structure, which leads to high computing costs, protracted training times, especially for large datasets, overfitting, and lack of interpretability.

In order to identify people who could be dyslexic, a computational tool called DysDTool is provided [6]. It is based on neural networks. The backpropagation approach of identifying people with learning challenges is intended to be supported by the tool, which was developed using Java technology, the Tomcat application server, and the MySQL database. The study only included 52 participants, which is a very small sample size, therefore the results might not generalize to the wider population. The study only contained a restricted age group and demographic, thus more testing with a larger and more diverse sample is needed to assess the effectiveness of the tools.

The dyslexia detection system in [7]is built on the Kernel Density Estimation (KDE) algorithm and an Artificial Neural Network (ANN) with Multi-Layer Perception (MLP). The outcomes of the Gibson test of cognitive capacities are assessed and investigated using computational three classifiers—K-means, ANN, and Fuzzy. The classifier output can differentiate between the three groups of people: healthy or normal (no dyslexia), dyslexic and other disorders. The results from the classifiers may distinguish between the three separate groups. Although the system may be difficult for some people to comprehend and use due to the usage of numerous classifiers and algorithms, the results from the classifiers can be discerned between the three separate classifications.

The study [8] investigates the use of machine learning to detect dyslexia in readers by analyzing eye-tracking data. In order to identify between those who have dyslexia and those who do not, the study established a technique for non-invasive dyslexia screening that makes use of distinctive features produced by eye-tracking data. It can be expensive and needs specialized equipment, making it difficult to implement extensively. Also, the Eye-tracking techniques that interfere with regular reading could influence the data accuracy.

The paper [9] describes a technique for diagnosing dyslexia in children using functional magnetic resonance imaging (fMRI) images. The approach includes preprocessing fMRI scans, creating Statistical Parametric Mapping (SPMs), and categorizing the data using a 3D Convolutional Neural Network (3D CNN). However, setting up fMRI scans and creating Statistical Parametric Mapping (SPMs) is a difficult process that necessitates specific education and training. Due to the high cost and limited availability of fMRI scans, the approach is less applicable for widespread use.

A machine learning-based dyslexia screening tool called DysLexML [10] is presented. It creates a computational model that can precisely identify dyslexia in people. To assess the chance that a person has dyslexia, the program analyses data from numerous sources, including written text and audio recordings, using machine learning techniques. The findings of their tests indicate that the DysLexML tool may accurately and successfully screen for dyslexia, offering a potential new method for dyslexia evaluation. The study's limitations, however, are its small sample size and the requirement for additional research to validate the findings and investigate the tool's possible applicability in real-world situations.

A method for early dyslexia screening proposed by Spoon and Katie [11] makes use of unstructured handwriting samples from children. The study emphasizes the possibility of a more accurate and user-friendly way of assessing dyslexia, as the suggested model demonstrated a high accuracy rate when compared to existing approaches. However, the study is constrained by the small sample size, the narrow range of the handwriting data employed, and the absence of independent validation. In addition, there is a chance of making a false diagnosis if the model is applied without adequate validation or professional interpretation.

DxDetekt based on the Ensemble of CNN and CNN -LSTM networks for dyslexia detection from handwriting data leverages the strengths of these machine learning models and this approach offers a more objective and accessible method for dyslexia detection compared to traditional psychometric tests and techniques like fMRI scans and eye tracking. The CNN component of the model can extract relevant features from the handwriting data, while the LSTM component captures temporal relationships, resulting in a sophisticated representation of the child's writing ability. This eliminates the need for specialized equipment or personnel and does not interfere with the normal reading process, making it more feasible for widespread use. Overall, this approach has the potential to improve dyslexia diagnosis and early intervention efforts, leading to better outcomes for children with dyslexia.

III. MOTIVATION

Dyslexia is a common neurodevelopmental disorder that affects the ability to read, write, and spell accurately. Early detection and intervention can greatly improve outcomes for individuals with dyslexia, as it allows for tailored interventions to improve their reading and writing skills. Handwriting is an important aspect of literacy and can provide valuable insights into an individual's cognitive and motor skills. Therefore, developing an accurate and efficient method for detecting dyslexia from handwriting can contribute to early identification and intervention, ultimately benefiting individuals with dyslexia and society as a whole.

There have been significant advancements in the field of deep learning and handwriting analysis, which have motivated the development DxDetekt. CNNs have shown remarkable success in various computer vision tasks, including image classification, object detection, and feature extraction. LSTM) networks, on the other hand, making them suitable for time-series data like handwriting. By combining the strengths of CNNs and LSTMs, a CNN-CNN-LSTM model can leverage both local and global features from handwriting images and capture the temporal dynamics of writing, making it a promising approach for dyslexia detection from handwriting.

IV. PROBLEM DOMAIN

DxDetekt encompasses various areas of research and technology, including dyslexia, handwriting analysis, CNNs, LSTMs, ensemble learning, and data preprocessing and model evaluation.

V. PROBLEM DEFINITION

The problem addressed by DxDetekt is the need for a reliable and accurate method to detect dyslexia from handwriting samples. As in the case of Dyslexia, early detection is critical for timely intervention and support, existing methods for dyslexia detection may have limitations in terms of accuracy and robustness. Therefore, DxDetekt aims to fill this gap by leveraging the power of deep learning, specifically CNNs, and LSTMs, in analyzing the intricate features, patterns, and dynamics of handwriting DxDetekt is designed to enhancing the accuracy and robustness of the detection system, while also incorporating data preprocessing and model evaluation techniques to ensure reliable performance. The problem definition for DxDetekt revolves around developing an innovative solution that can effectively and efficiently detect dyslexia from handwriting, aiding in early identification and intervention for individuals with dyslexia.

VI. STATEMENT

"Developing an Accurate and Reliable Dyslexia Detection System from Handwriting using CNN-CNN-LSTM Ensemble Approach"

VII. METHODOLOGY

The methodology used for DxDetekt can be summarized as follows:

A. Data Collection

Collected a large dataset of handwriting samples from individuals with and without dyslexia.

B. Data Preprocessing

Preprocessed the handwriting images by converting them to grayscale, resizing them to a standard size, and normalizing the pixel values.

C. Data Augmentation

Augmented the dataset by applying various transformations such as rotation, scaling, and flipping to generate additional samples.

D. Model Architecture

Designed an ensemble model that combines the strengths of CNN and CNN LSTM models.

E. Training

Trained the ensemble model using the preprocessed and augmented dataset. Used loss function binary cross-entropy, and optimized the model using Adam optimizer.

F. Evaluation

Evaluated the performance of the model using various metrics such as accuracy, precision, recall, and F1-score.

G. Fine-tuning

Fine-tuned the model by adjusting the hyperparameters.

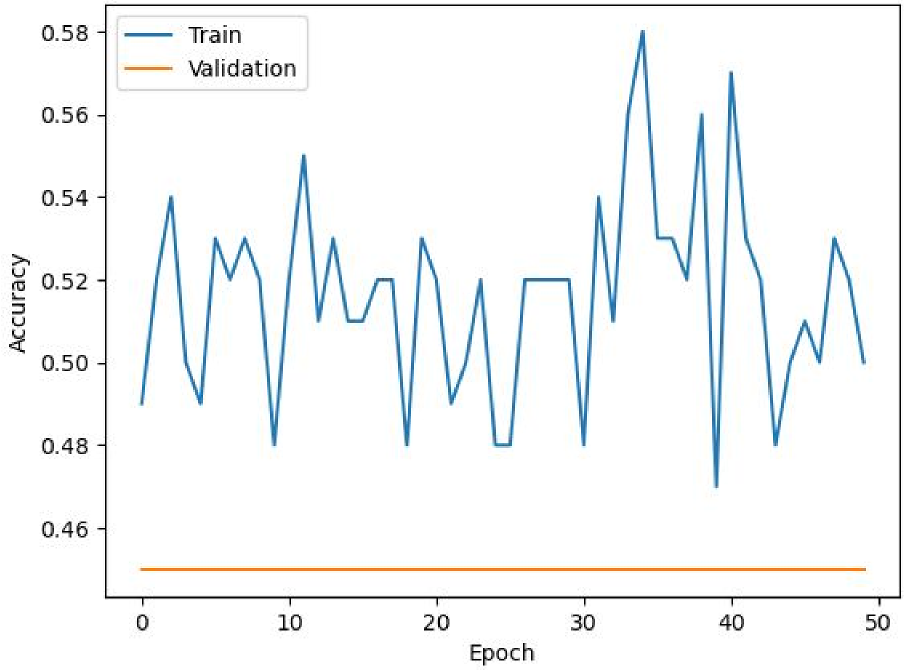

Figure 2: Accuracy of LSTM Model

VIII. System Architecture

A Convolutional Neural Network (CNN) is a type of deep learning algorithm that is designed to automatically learn and extract relevant features from image data. The architecture of a CNN model is composed of multiple layers, including convolutional, pooling, and fully connected layers. The convolutional layers are responsible for extracting local spatial features from the input image by convolving a set of filters over the image. Each filter is a set of learnable weights that convolve with the image, producing a feature map that highlights the presence of specific features in the image. Multiple filters are used in each convolutional layer to detect different features.

Pooling layers are used to reduce the spatial dimensions of the feature maps produced by the convolutional layers. Max pooling is a commonly used pooling technique that selects the maximum value within a specified window size. The fully connected layers take the flattened feature maps as input and pass them through a set of densely connected layers to produce the output classification.

CNN models are trained using backpropagation, where the weights of the filters and fully connected layers are updated based on the error between the predicted output and the true output. The training process involves adjusting the weights of the network to minimize the error and improve the accuracy of the model.

In the context of dyslexia detection from handwriting images, a CNN model can be trained to learn the relevant patterns and features that indicate dyslexia. By analyzing the handwriting features extracted by the CNN model, we can identify dyslexia-related anomalies in handwriting patterns. This approach has the potential to provide a reliable, automated, and efficient way to detect dyslexia in individuals. However, this model had difficulty in handling temporal information related to dyslexia. To overcome this limitation, a CNN-LSTM model was introduced, which was better suited for processing temporal data.

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) that was introduced to address the problem of vanishing gradients in traditional RNNs. LSTMs were designed to selectively remember or forget previous inputs based on the current input, which makes them better suited for modelling long-term dependencies in sequential data.

An LSTM cell consists of three main components: the input gate, the forget gate and the output gate. These gates are responsible for selectively controlling the flow of information into and out of the LSTM cell. The input gate determines which information from the current input should be stored in the cell state. The forget gate determines which information from the previous cell state should be discarded. The output gate determines which information from the cell state should be output to the next cell or the final output. The cell state in an LSTM network acts as a kind of memory that can store information over long periods of time. The gates in the LSTM network allow the model to selectively update and forget information in the cell state based on the input and previous state.

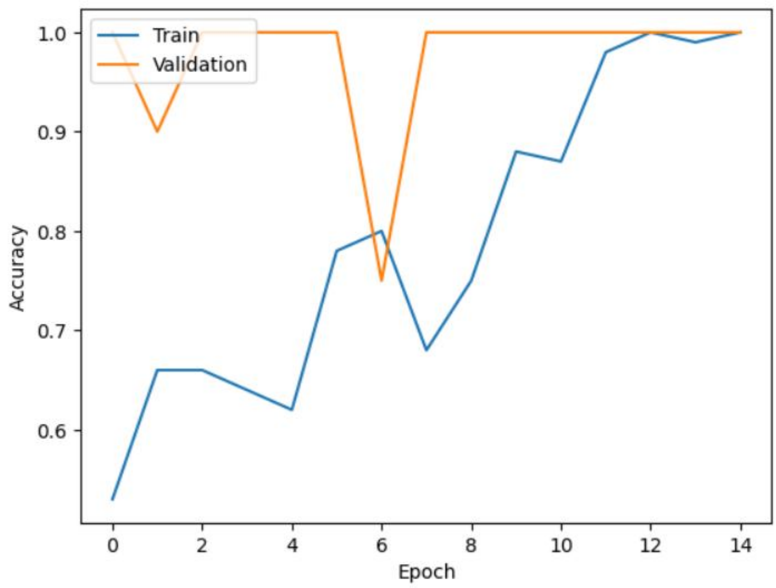

Figure 3: Accuracy of DxDetekt

In the context of dyslexia detection from handwriting images, a CNN-LSTM model can be trained to learn the relevant patterns and features that indicate dyslexia in both the spatial and temporal domains. This is achieved by utilizing the CNN component of the model to extract spatial features from the input handwriting image, and the LSTM component to analyze the sequence of these features over time. The CNN component takes the input handwriting image and extracts relevant spatial features using convolutional layers. The output of the CNN component is a set of feature maps that highlight the presence of specific features in the image.

The LSTM component takes the output feature maps from the CNN and analyzes them over time using LSTM layers. The LSTM component can effectively capture the temporal dependencies and relationships between the extracted spatial features, providing a more complete representation of the handwriting data.

The output of the LSTM component is then passed through a fully connected layer to produce the final dyslexia detection result. The fully connected layer takes the LSTM output as input and produces a binary classification result indicating the presence or absence of dyslexia. Overfitting and low accuracy are the two challenges faced by this model as shown in Figure 3.

To address these limitations, the ensemble approach-DxDetekt - was implemented by combining the strengths of both models. This ensemble approach allowed the model to effectively handle both spatial and temporal features

of dyslexia-related handwriting patterns. By leveraging the advantages of both CNN and CNN-LSTM, the ensemble model has demonstrated high accuracy in detecting dyslexia from handwriting data.
The CNN model comprises three convolutional layers with 32 filters of size 3x3 each. The convolutional layers are followed by tanh activation and max-pooling layers, which help in reducing the dimensionality of the feature maps. The output of the final convolutional layer is flattened and fed into two fully connected layers, which have 256 and 1 neuron, respectively. The activation function for the first fully connected layer is ReLU, while the output layer uses sigmoid activation to classify the input sample as dyslexic or non-dyslexic.
The CNN-LSTM model uses the same three convolutional layers as the CNN model. However, instead of a fully connected layer, the output of the final convolutional layer is passed through a time-distributed layer, which is then fed into an LSTM layer. The LSTM layer has 32 neurons, which capture the temporal dependencies in the input handwriting sequence. The output of the LSTM layer is then passed through two fully connected layers, which have 128 and 2 neurons, respectively. The activation function for the first fully connected layer is tanh, and a dropout layer with a dropout rate of 0.5 is added before the output layer, which uses SoftMax activation to classify the input sample as dyslexic or non-dyslexic.
The output of both models is combined using an ensemble approach to improve the accuracy of dyslexia detection. The output of the second-last layer of both models is concatenated, and the concatenated output is passed through two fully connected layers, which have 128 and 1 neurons, respectively. The activation function for the first fully connected layer is ReLU and a dropout layer with a dropout rate of 0.5 is added before the output layer, which uses sigmoid activation to classify the input sample as dyslexic or non-dyslexic.
The proposed system was trained and evaluated using a dataset of handwriting samples from dyslexic and non-dyslexic individuals. The dataset was split into training and validation sets, and the system was trained using the binary cross-entropy loss function and the Adam optimizer. The system achieved high accuracy, sensitivity, and specificity in detecting dyslexia from handwriting samples.

IX. RESULT

Based on the results obtained from the DxDetekt dyslexia detection model, it can be concluded that the ensemble model consisting of a CNN and an LSTM outperforms the individual models. The precision, recall, and F1 score were 1.0, 0.846, and 0.917, respectively. The model also achieved an accuracy above 90 percent as shown in fig 4, indicating that it can accurately detect dyslexia from handwriting.

X. CONCLUSION AND FUTURE SCOPE

DxDetekt is a promising tool for accurately diagnosing dyslexia based on handwriting samples. With further improvements and validation, this model has the potential to significantly contribute to the early detection and intervention of dyslexia, improving the academic and social outcomes of individuals with dyslexia.
The model can be further improved by incorporating more advanced techniques such as transfer learning or finetuning pre-trained models on larger datasets. Additionally, more data can be collected to further train and validate the model, which can improve its accuracy and generalization performance.
Furthermore, the model can be adapted for real-world applications such as developing a mobile app that can analyze a person’s handwriting and detect dyslexia. This can help in the early detection and intervention of dyslexia, which can significantly improve a person’s academic and social outcomes. Additionally, the model can be extended to analyze other aspects of handwriting such as handwriting speed, pressure, and stroke pattern, which can provide more comprehensive insights into a person’s handwriting and related disorders.
Another potential future scope of the model is to detect the level of dyslexia in individuals. Dyslexia can vary in severity, and detecting the level of dyslexia can help in tailoring interventions and support to meet the individual’s specific needs. This can be achieved by collecting additional data that includes information on the severity of dyslexia in individuals and training the model to classify individuals into different severity levels.
Another area of future scope is to integrate the model with other assistive technologies such as text-to-speech software or speech recognition systems. This can provide a more holistic approach to dyslexia management and support individuals with dyslexia in different aspects of their daily lives.
Overall, the potential applications and future scope of the dyslexia detection model are promising and can significantly contribute to improving the quality of life of individuals with dyslexia.

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