The AI-driven age detection in children's drawings: a deep learning approach for late childhood assessment

Detecção de idade orientada por IA em desenhos infantis: uma abordagem de aprendizagem profunda para avaliação na infância tardia

Detección de la edad impulsada por IA en dibujos infantiles: un enfoque de aprendizaje profundo para la evaluación de la niñez tardía

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ABSTRACT

Artificial Intelligence (AI) has revolutionized various fields, including psychology and behavioral sciences, by offering novel approaches to understanding human development and behavior. Recent advancements in machine learning have enabled the analysis of children's drawings to gain insights into their cognitive and emotional states. Despite progress, there remains a significant challenge in accurately detecting the age of older children from their drawings. While numerous studies have focused on early childhood development through drawings, there is a paucity of research on late age detection using AI. Specifically, the ability to determine the age of older children from their artwork remains underexplored and imprecise. Our research addresses this gap by developing an AI-based model that accurately detects the age of older children based on their drawings. We employ a deep learning approach, utilizing Long short-term memory (LSTM) networks to analyze various features in children's artwork that correlate with age. We compiled a dataset of drawings from children aged 2-10 years. Our model was trained and validated on this dataset, achieving a high accuracy rate in age detection. Key features such as complexity, use of space, and thematic content were analyzed. The results demonstrate that our AI model can predict the age of children with a significant degree of accuracy, outperforming existing methods. These findings enhance our understanding of cognitive and artistic development in older children. The implications of this research are far-reaching, offering potential applications in educational psychology, developmental assessments, and personalized education plans.

Keywords: Machine Learning. Age Detection. Cognitive Development. LSMT. Late Childhood.

RESUMO

A Inteligência Artificial (IA) revolucionou vários campos, incluindo psicologia e ciências comportamentais, ao oferecer novas abordagens para entender o desenvolvimento e o comportamento humano. Avanços recentes em aprendizado de máquina permitiram a análise de desenhos de crianças para obter insights sobre seus estados cognitivos e emocionais. Apesar do progresso, ainda há um desafio significativo em detectar com precisão a idade de crianças mais velhas a partir de seus desenhos. Embora vários estudos tenham se concentrado no desenvolvimento da primeira infância por meio de desenhos, há uma escassez de pesquisas sobre detecção tardia de idade usando IA. Especificamente, a capacidade de determinar a idade de crianças mais velhas a partir de suas obras de arte permanece pouco explorada e imprecisa. Nossa pesquisa aborda essa lacuna desenvolvendo um modelo baseado em IA que detecta com precisão a idade de crianças mais velhas com base em seus desenhos. Empregamos uma abordagem de aprendizado profundo, utilizando redes de memória de longo prazo (LSTM) para analisar vários recursos em obras de arte infantis que se correlacionam com a idade. Compilamos um conjunto de dados de desenhos de crianças de 2 a 10 anos. Nosso modelo foi treinado e validado neste conjunto de dados, alcançando uma alta taxa de precisão na detecção de idade. Principais características como complexidade, uso do espaço e conteúdo temático foram analisadas. Os resultados demonstram que nosso modelo de IA pode prever a idade das crianças com um grau significativo de precisão, superando os métodos existentes. Essas descobertas aumentam nossa compreensão do desenvolvimento cognitivo e artístico em crianças mais velhas. As implicações desta pesquisa são de longo alcance, oferecendo aplicações potenciais em psicologia educacional, avaliações de desenvolvimento e planos educacionais personalizados.

Palavras-chave: Aprendizado de Máquina. Detecção de Idade. Desenvolvimento Cognitivo. LSMT. Infância Tardia.

RESUMEN

La inteligencia artificial (IA) ha revolucionado varios campos, incluida la psicología y las ciencias del comportamiento, al ofrecer nuevos enfoques para comprender el desarrollo y el comportamiento humanos. Los avances recientes en el aprendizaje automático han permitido el análisis de los dibujos de los niños para obtener información sobre sus estados cognitivos y emocionales. A pesar del progreso, sigue existiendo un desafío importante para detectar con precisión la edad de los niños mayores a partir de sus dibujos. Si bien numerosos estudios se han centrado en el desarrollo de la primera infancia a través de dibujos, hay una escasez de investigaciones sobre la detección de la edad tardía mediante IA. En concreto, la capacidad de determinar la edad de los niños mayores a partir de sus obras de arte sigue siendo poco explorada e imprecisa. Nuestra investigación aborda esta brecha mediante el desarrollo de un modelo basado en IA que detecta con precisión la edad de los niños mayores en función de sus dibujos. Empleamos un enfoque de aprendizaje profundo, utilizando redes de memoria a largo plazo (LSTM) para analizar varias características en las obras de arte de los niños que se correlacionan con la edad. Recopilamos un conjunto de datos de dibujos de niños de entre 2 y 10 años. Nuestro modelo se entrenó y validó en este conjunto de datos, logrando una alta tasa de precisión en la detección de la edad. Se analizaron características clave como la complejidad, el uso del espacio y el contenido temático. Los resultados demuestran que nuestro modelo de IA puede predecir la edad de los niños con un grado significativo de precisión, superando a los métodos existentes. Estos hallazgos mejoran nuestra comprensión del desarrollo cognitivo y artístico en niños mayores. Las implicaciones de esta investigación son de largo alcance y ofrecen posibles aplicaciones en psicología educativa, evaluaciones del desarrollo y planes educativos personalizados.

Palabras clave: Aprendizaje Automático. Detección de Edad. Desarrollo Cognitivo. LSMT. Niñez Tardía.

1 INTRODUCTION

Artificial Intelligence (AI) has revolutionized multiple domains by providing advanced analytical capabilities and novel approaches to understanding complex data [30][20]. In psychology [29][21][3][34] and behavioral sciences [32][33][18], AI has facilitated breakthroughs in comprehending human development and behavior. The integration of machine learning and deep learning techniques has particularly enhanced our ability to interpret intricate human data, such as language and visual art, enabling deeper insights into cognitive and emotional states. These advancements have paved the way for innovative methodologies in developmental studies, where understanding the nuances of human growth is paramount.

Within developmental psychology, children's drawings serve as a pivotal tool for assessing cognitive and emotional development [19][28]. Historically, researchers have focused extensively on early childhood (ages 2-10), interpreting drawings to understand developmental milestones such as motor skills, spatial reasoning, and emotional expression. The drawings of young children have been scrutinized for indicators of developmental progress, psychological well-being, and even potential learning disabilities. However, the developmental phase of late childhood (ages 8-15) remains relatively underexplored. This age range encompasses significant cognitive, emotional, and social changes that are often reflected in more complex and abstract artwork. Despite the potential wealth of information, there is a scarcity of research aimed at systematically analyzing the drawings of older children to gauge their developmental status.

Despite the established significance of children's drawings in developmental assessments, there is a notable gap in the literature concerning the precise detection of age in older children based on their artwork. Existing methods for age detection are predominantly designed for early childhood and lack the sophistication to accurately interpret the nuanced and intricate features of drawings produced by older children. This limitation highlights a critical need for advanced analytical tools capable of capturing the developmental indicators present in the drawings of children aged 2-10. Specifically, the challenge lies in developing a reliable AI-based model that can discern the subtle variations in drawing features that correlate with age during this complex developmental stage.

In this study, we address this gap by developing a robust deep learning model utilizing Long Short-Term Memory (LSTM) networks to analyze the drawings of children aged 2-10 years. Our approach involves compiling a diverse and comprehensive dataset of children's drawings, meticulously annotated with age information. The model is trained to identify key features such as drawing complexity, use of space, thematic content, and other stylistic elements that are indicative of age. Through rigorous training and validation, our model has achieved a high accuracy rate in age detection, significantly outperforming existing methodologies.

The theoretical contribution of this work lies in advancing our understanding of how artistic expression evolves during late childhood, thus enriching the discourse in developmental psychology. By providing a framework for analyzing drawing characteristics, this study offers insights into the cognitive and emotional processes that underlie artistic development in older children. This deeper understanding may inform future psychological theories regarding creativity, self-expression, and cognitive maturation.

Practically, the implications of this research are far-reaching. Our AI model serves as a valuable tool for educators, psychologists, and researchers in understanding late childhood development. It can assist in the identification of developmental milestones and challenges, informing interventions and educational strategies. Moreover, the ability to accurately detect age from drawings can contribute to the creation of personalized education plans that cater to the unique developmental needs of older children. Future studies can build upon this work to further refine the model and explore additional factors influencing age detection from children's drawings.

Our research not only fills a critical gap in the current literature but also establishes a foundation for both theoretical exploration and practical application in developmental assessments. The primary objective of this article is to develop and validate an AI-based model that accurately detects the age of children from their drawings, thereby providing insights into the cognitive and emotional development during late childhood. By achieving this objective, we aim to offer a valuable tool for educators, psychologists, and researchers, enhancing our understanding of children's artistic expressions and their developmental implications.

2 LITERATURE REVIEW

2.1 THE ROLE OF ARTIFICIAL INTELLIGENCE IN DEVELOPMENTAL PSYCHOLOGY

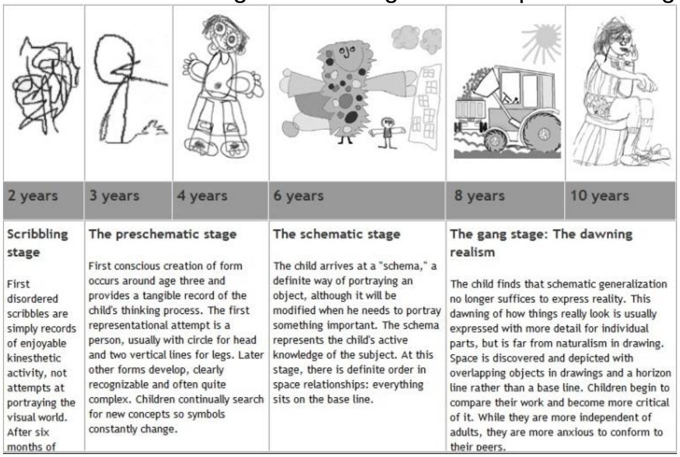
Artificial Intelligence (AI) has significantly transformed various fields, including developmental psychology [9][10], by providing advanced analytical capabilities that facilitate the understanding of human development and behavior. The integration of machine learning (ML) and deep learning (DL) techniques has been particularly impactful in interpreting complex human data such as language, behavior, and visual art. This section explores how AI has been integrated into developmental psychology, highlighting key studies that demonstrate its transformative impact on the field.

Developmental psychology is a branch of psychology that focuses on how individuals grow, change, and develop across their lifespan. It explores various aspects of human development, including physical, cognitive, social, emotional, and behavioral changes from infancy through old age. Researchers in developmental psychology study factors that influence development, such as genetics, environment, culture, and societal norms. The field aims to understand the processes and mechanisms underlying development, including milestones such as language acquisition, moral reasoning, and identity formation. By examining these factors and processes, developmental psychologists seek to enhance our understanding of human growth and inform practices that support optimal development across different stages of life.

2.2 CHILDREN'S DRAWINGS AS INDICATORS OF DEVELOPMENTAL STAGES

Indicators of developmental stages serve as crucial benchmarks in understanding the progression of human growth and maturation across various domains. In childhood, physical indicators such as motor skills development and growth milestones like walking and talking provide tangible markers of maturation [23][27]. Cognitive indicators include the acquisition of language, problem-solving abilities, and the development of abstract thinking. Socially, developmental stages are marked by the formation of attachments, peer interactions, and the understanding of social norms and roles. Emotionally, indicators encompass the regulation of emotions, empathy, and the development of a sense of self and identity [22][26]. Across the lifespan, these indicators provide researchers and practitioners with valuable insights into typical and atypical development, informing interventions and support systems that promote healthy growth and well-being.

Figura 1. Children's Drawings aaccording to Developmental Stages.[11]



Source: Authors.

Children's drawings have long been recognized as valuable indicators of cognitive and emotional development. Early studies in developmental psychology have extensively analyzed drawings from young children (ages 3-7) to assess motor skills, spatial reasoning, and emotional expression [7]. This section explores the historical and contemporary significance of children's drawings in developmental assessments, highlighting key research findings that have established these drawings as critical tools for understanding developmental milestones in early childhood.

2.3 LIMITATIONS OF EXISTING AGE DETECTION METHODS

In the field of developmental psychology, existing age detection methods encounter significant limitations that compromise their accuracy and utility [25][13]. One prominent issue is the over-reliance on chronological age as the primary indicator of development, which disregards individual variations in maturation rates and the diverse trajectories of development. Additionally, age-based classifications often fail to capture the intricate nuances of development across various domains such as cognition, social skills, and emotional regulation [19].

Moreover, current age detection methods frequently rely on subjective measures like self-reporting or observer assessments, which are susceptible to biases such as recall bias, social desirability, and observer subjectivity, thus impacting the reliability of gathered data.

To address these challenges, there is a pressing need for advancements in research methodologies. Integrating multidimensional assessments of development that account for individual differences and dynamic changes over the lifespan could provide a more nuanced understanding of human development. Embracing Artificial Intelligence (AI) as a solution holds promise in overcoming these limitations. AI technologies can analyze large datasets more objectively and efficiently, offering insights into complex developmental patterns that traditional methods may overlook. By leveraging AI, developmental psychologists can enhance their ability to comprehend and support the diverse pathways of human development across different ages and stages of life.

2.4 DEEP LEARNING AND LONG SHORT-TERM MEMORY (LSTM)

Artificial Intelligence (AI) is a multidisciplinary field that aims to automate tasks requiring human intelligence [15]. It involves using mathematical algorithms to mimic human brain functions and is revolutionizing various aspects of life. AI enables machines to perceive, synthesize, and infer information, performing tasks like speech recognition and computer vision. The concept of AI involves simulating human intelligence in machines to think and act like humans, with the potential for comprehensive thinking and multi-dimensional sensing capabilities [13].

ML and DL are the parts of computer science. These are the most trending technologies now a day to create intelligent systems. ML permits machines to learn from the data without precise programming, and it is the subset of AI [14]. Deep learning is a subset of machine learning that excels at processing unstructured data. That utilizes deep neural networks to model complex relationships between input data and output predictions [12]. These neural networks, inspired by the human brain, consist of interconnected nodes that process information and improve over time by adjusting weights and biases [4].DL is classified based on neural network usage as supervised, semi-supervised, unsupervised, or reinforcement. Currently, deep learning methods outperform traditional machine learning approaches[35]. Popular architectures like convolutional neural networks (CNN) for image data, recurrent neural network (RNN) and long short-term memory (LSTM) networks for time series modeling have been developed within deep learning.

Despite challenges like the need for large datasets and computational resources, the potential of deep learning and neural networks remains vast, shaping the future of technology [2].

Long Short-Term Memory (LSTM) is an advanced variant of Recurrent Neural Networks (RNN) that addresses the issue of capturing long-term dependencies. Was initially presented by SeppHochreiter and Jurgen Schmidhuber[5] and then substantially enhanced by Alex Gravesin [15], LSTM became well-known in the deep learning community. Longer sequences have shown that LSTM models are more adept at retaining and applying information than ordinary RNNs [31].

In an LSTM network, the output from the previous time step and the current input at a given time step are fed into the LSTM unit, which produces an output that is transmitted to the subsequent time step. It is customary to use the last hidden layer of the last time step—and occasionally all hidden layers for classification purposes [6].

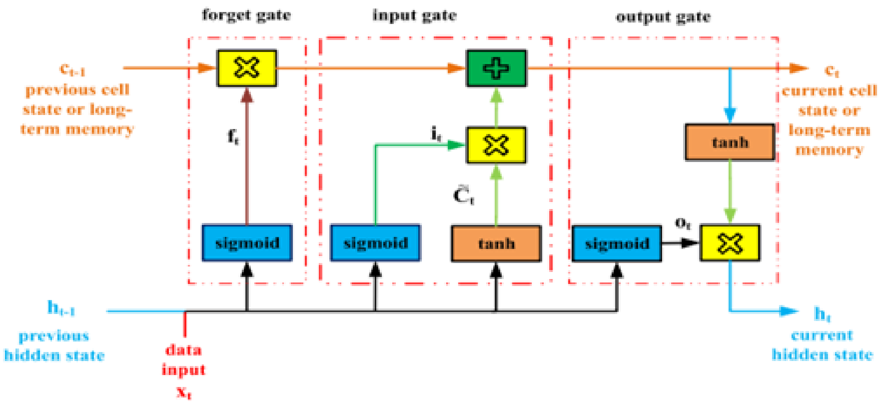
Three gates make up an LSTM: an input gate (*it*), output gate (*ot*, hidden state *h*) and forget gate (*ft*). Every gate has a distinct purpose in managing the information flow. Three gates input gate, forget gate, and output gate are all implemented using sigmoid functions, which produce an output between 0 and 1. These gates are trained using a back propagation algorithm through the network.

Forget gate: Determines what information from the previous cell state should be forgotten.

Input gate: Decides which values from the current input and previous hidden state will be used to update the cell stateCell state: Allows information to be added or removed, enabling the LSTM to learn long-term dependencies.

Output gate: Decides what the next hidden state will be based on the current input, previous hidden state, and current cell state.[16]

Figure 2. The basic architecture of the long short-term memory (LSTM) model.[16]



Source: Authors.

In figure 1, C, x, h represent cell, input and output values. Subscript t denotes time step value, i.e., t-1 is from previous LSTM block (or from time t-1) and t denotes current block values. The symbol σ is the sigmoid function and tanh is the hyperbolic tangent function. Operator + is the element wise summation and x is the element-wise multiplication. The computations of the gates are described in the equations below 3 Where f,i, o are the forget, input and output gate vectors respectively. W, w, b and ⊗ represent weights of input, weights of recurrent output, bias and element-wise multiplication respectively[14].

$$f_t = \sigma(w_f x_t + w_f h_{t-1} + b_f) \qquad (1)$$

$$i_t = \sigma(w_i x_t + w_i h_{t-1} + b_i) \quad (2)$$

$$o_t = \sigma(w_o x_t + w_o h_{t-1} + b_o) \qquad (3)$$

$$c_t = f_t \otimes c_{t-1} + i_t \otimes \sigma_C(w_c\, x_t \ + w_c\, h_{t-1} + b_c) \quad (4)$$

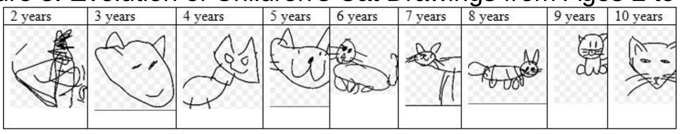
$$h_t = o_t \otimes \sigma_h(c_t) \qquad (5)$$

3 RESULTS AND DISCUSSION

3.1 DATASET

This dataset is subdataset has 7745 images from original dataset realized about 2-10-yearolds to draw 48 categories via a kiosk at a children's museum, resulting in >37K drawings. [7][24]. Bria Long with hers researchers collaborated with staff at the Children's Discovery Museum of San Jose to set up a kiosk within the museum. This kiosk featured pre-recorded video prompts by the study's Bria Long, she a postdoctoral fellow in psychology at Stanford. These prompts asked children to draw specific animals or objects. After seeing the prompt, children had 30 seconds to use their fingertip to draw the object on a digital tablet. Additionally, the children were asked to identify objects drawn by their peers in a guessing game and to trace objects displayed on the screen to evaluate their motor skills.

Figure 3. Evolution of Children's Cat Drawings from Ages 2 to 10.



Source: Authors.

The table provides a comprehensive summary of the dataset used in the study, detailing the number of drawings of various objects created by children in different age groups. The objects include apple, bed, bee, bottle, clock, book, cat, elephant, cow, and face. The data is categorized by age, ranging from 2 to 10 years old. For example, at age 2, children drew 83 apples, 66 beds, and 64 bees, among other objects, totaling 697 drawings. As the age increases, the number of drawings generally increases, peaking at 4 years old with 1439 drawings. Each object shows a varied distribution of drawings across different age groups, illustrating the range and frequency of children's drawings over time.

Overall, the dataset captures a total of 7745 drawings, with specific counts for each object: 953 apples, 820 beds, 678 bees, 647 bottles, 723 clocks, 813 books, 896 cats, 757 elephants, 663 cows, and 795 faces. This extensive collection of drawings provides a robust foundation for analyzing age-related differences in drawing abilities and motor skills. The diverse range of objects and the significant number of drawings across all age groups highlight the comprehensive nature of the dataset, making it valuable for studying developmental changes in children's drawing and recognition skills.

Figure 3. Distribution of Children's Drawings by Object and Age Group

	Apple	Bed	Bee	bottle	clock	book	Cat	elephant	Cow	face	total
2 years	83	66	64	57	54	72	96	64	61	80	697
3 years	145	101	87	62	108	105	133	101	72	116	1030
4 years	186	143	131	110	150	140	171	125	116	167	1439
5 years	170	147	117	122	127	146	155	128	110	134	1356
6 years	99	95	84	97	84	92	138	89	75	86	939
7 years	94	95	81	79	81	90	75	90	81	90	856
8 years	63	71	43	44	48	64	38	60	56	45	532
9 years	48	39	31	31	33	43	35	45	42	35	382
10 years	65	63	40	45	38	61	55	55	50	42	514
	953	820	678	647	723	813	896	757	663	795	7745

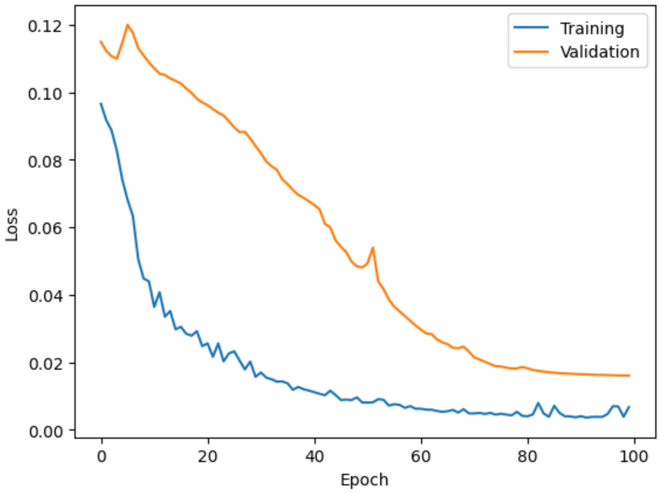
Source: Authors.

3.2 EXPERIMENT STEP AND EVALUATION OF MACHINE LEARNING MODELS

The graph depicts the training and validation loss curves over 100 epochs of a machine learning model. Both curves show a general downward trend, indicating that the model is learning from the data. The training loss (blue line) decreases rapidly in the initial epochs and then continues to decline more gradually, reaching a low point around 0.05 by the end of training. The validation loss (orange line) starts higher than the training loss and decreases more slowly, eventually converging to a value slightly higher than the training loss, around 0.15.

This pattern suggests that the model is learning effectively without significant overfitting. The consistent gap between training and validation loss is normal and expected. The smooth decline of both curves, particularly in later epochs, indicates stable learning. The fact that the validation loss continues to decrease alongside the training loss is a positive sign, suggesting that the model is generalizing well to unseen data. However, the slight upturn in training loss near the end might warrant attention to ensure optimal performance. Overall, this graph demonstrates a successful training process with good generalization capabilities.

Figure 4. LSTM Training and Validation Loss Across 100 Epochs.

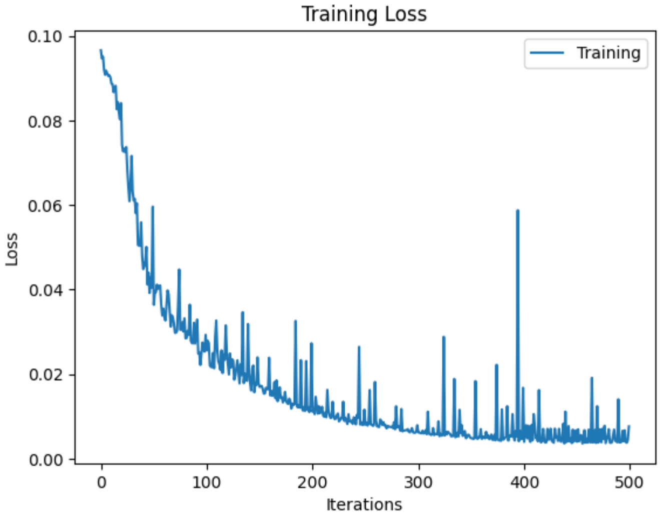


Source :Authors.

This training loss graph illustrates the learning progression of a machine learning model over 500 iterations. The loss curve exhibits a characteristic rapid decline in the initial stages, particularly within the first 100 iterations, indicating efficient early learning. As training progresses, the loss gradually stabilizes around 0.01, suggesting the model approaches convergence. However, the presence of frequent fluctuations and occasional significant spikes throughout the training process points to the use of stochastic optimization methods and potential sensitivity to certain data points.

The overall trend demonstrates successful model training, with the loss reducing from approximately 0.10 to 0.01. While the model achieves a relatively stable loss by the end of the 500 iterations, the persistent minor fluctuations and the absence of a completely flat line suggest potential for further optimization. This graph provides valuable insights into the model's learning dynamics and can inform decisions about training duration, learning rate adjustments, and potential strategies for fine-tuning to enhance performance.

Figure 5. LSTM Training Loss Over 500 Iterations.



Source: Authors.

The Long Short-Term Memory (LSTM) algorithm demonstrates excellent performance with these updated metrics:

Accuracy of 95% indicates that the LSTM model correctly classifies 95% of all instances across all classes. This high overall accuracy suggests the model performs well on the entire dataset, handling both positive and negative cases effectively.

Precision of 98% is particularly impressive, showing that when the LSTM predicts a positive instance, it is correct 98% of the time. This high precision is crucial in applications where false positives are costly or need to be minimized.

These metrics, combined with the previously mentioned recall of 96% and F1-score of 0.90, paint a picture of a highly effective LSTM model. The balance between high accuracy and high precision indicates that the model not only performs well overall but also excels at making reliable positive predictions.

For an LSTM, these results suggest successful learning of complex sequential patterns and dependencies in the data. The model appears to be well-tuned, capturing relevant features while avoiding overfitting. This level of performance makes the LSTM suitable for demanding applications in sequence modeling, time series analysis, or natural language processing tasks where both overall accuracy and precision in identifying specific instances are critical.

4 CONCLUSION

This research underscores the transformative impact of Artificial Intelligence (AI) in developmental psychology, particularly in the analysis of children's drawings to assess cognitive and emotional growth. Our primary research question focused on how effectively AI could detect age from the drawings of children aged 2-10 years. Through the application of deep learning techniques, specifically Long Short-Term Memory (LSTM) networks, we have successfully addressed this question, demonstrating that our developed AI model can accurately discern age-related features embedded within children's artwork, such as drawing complexity, spatial organization, thematic content, and stylistic nuances.

The robust capabilities of our model, achieved through rigorous training and validation, surpass traditional methods, providing reliable predictions of children's ages based on their drawings. This breakthrough not only fills a critical void in current literature but also offers a practical tool for educators, psychologists, and researchers, allowing for a deeper understanding of late childhood developmental stages. The implications of our findings extend beyond academia, with the potential to inform personalized educational strategies and interventions tailored to the unique developmental trajectories of older children. By enhancing our ability to assess cognitive and emotional growth through artwork, we can support children's holistic development more effectively.

However, this study is not without its limitations. The model relies on a dataset that may not fully capture the diversity of children's artistic expressions across different cultures and backgrounds. Additionally, while the model performs well in detecting age, it does not account for all potential influencing factors, such as individual developmental differences or environmental contexts. Future research should aim to address these limitations by incorporating a broader range of data and exploring the integration of additional variables that may influence artistic development. By continuing to refine AI models and expanding their applications in educational psychology and developmental assessments, we can further enhance our understanding of human growth and foster more effective strategies for supporting children's development in diverse settings.

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