Interdisciplinary impact on animal cognition and human learning strategies using predictive modeling

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***Abstract* - This study focuses on the relationship between animal cognition and human learning. From decoding animal behaviors to enhancing human understanding, predictive modeling stands as a primary tool for bridging the gap between empirical observations and theoretical insights. The synthesis of findings from machine learning algorithms, and neural networks has led to an acknowledgment of animal cognition, including the anticipation of behaviors like migration, problem-solving, and social interactions. This synergy not only enhances learning outcomes but also offers a window into the shared evolutionary traits of cognition. The transition to human cognition explores how animal cognition models inform the creation of adaptive learning technologies, which mimic natural adaptive learning processes. Thereby, this encourages contributing a deeper understanding of mankind and their evolution using predictive modeling.**

Keywords - Predictive Modeling, Machine Learning, Artificial Intelligence, Adaptive Learning Systems.

I. INTRODUCTION

The exploration of cognitive relationships between great apes and humans is the central idea which revolves around understanding our shared evolutionary origins. As proposed by Charles Darwin, humans can be viewed as "big-brained apes," a perspective guiding our investigation into the commonalities of great apes and humans. This research delves into the exploration of the predictive modeling to dissect aspects such as social learning, problem-solving, memory, communication, emotional intelligence, cultural transmission, and self-awareness, shedding light on the evolutionary roots of human cognition.

Historical studies by Köhler and Yerkes demonstrated problem-solving abilities in chimpanzees. Gardner's ASL studies with Washoe in the 1960s showcased ape communication abilities, while Goodall's research revealed chimpanzees' tool use in the wild. Boesch and de Waal documented cultural variations in ape tool use and social behaviors, while Savage-Rumbaugh and Rumbaugh conducted comparative studies of ape and human cognition. Recent neuroscience techniques reveal similarities in brain structure and function between apes and humans, marking pivotal milestones in the study of cognitive evolution.

The research gap in human and animal cognition includes understanding the evolutionary steps leading to human language, the extent of cognitive capacities in non-human animals, cultural behaviors' complexity, the neurobiological basis of cognitive abilities, and the ecological context shaping cognitive evolution, an interdisciplinary approach is crucial. This integration spans cognitive psychology, neuroscience, ethology, anthropology, and comparative biology.

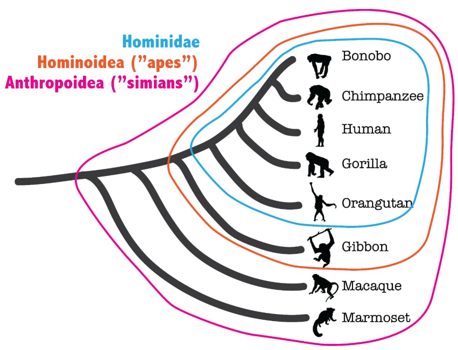

Fig 1 : Marching towards cognitive evolution

Building a predictive model for ape and human cognition involves collecting behavioral, neurological, and genetic data, utilizing Artificial Intelligence for analysis, and employing machine learning for modeling. Despite challenges like ethical considerations and the complexity of cognition, this interdisciplinary approach aims to identify cognitive commonalities and evolutionary pathways.

Predictive modeling in animal and human cognition is complex, involving challenges such as capturing diverse cognitive processes, incorporating contextual factors, addressing cross-species variability, ensuring model interpretability and generalization, and overcoming ethical and practical constraints. These complexities necessitate interdisciplinary collaboration, rigorous methodology, and careful experimental design consideration to advance our understanding of cognition across species.

II. LITERATURE REVIEW

E . Sue Savage-Rumbaugh, Jeannine Murphy, Rose A. Sevick, Karen E. Brakke, Shelly L. Williams, Duane M. Rumbaugh , "Language Comprehension in Ape and Child" emphasises the overlooked aspect of comprehension in language development. While past theories suggested that syntactic processing is uniquely human, the experiment compares the language comprehension skills of a 2-year-old child and an 8-year-old bonobo raised in a language-rich environment. Both subjects, exposed to spoken English and lexigrams through observational learning, were tested on 660 novel sentences. Surprisingly, the bonobo exhibited higher accuracy in decoding word recursion, suggesting potential cognitive capacities for language comprehension in non-human species. The results, discussed in the context of language evolution, propose that the ability for comprehension predates speech by millions of years, linking the onset of speech to adaptations in bipedalism and vocal tract reorientation. This physical adaptation enabled the evolution of a speech-like mode of communication in hominids.

Daniel A. Sternberg, Kacey Ballard, Joseph L. Hardy, Benjamin Katz, P. Murali Doraisamy and Michael Scanlon, "The largest human cognitive performance dataset reveals insights into the effects of lifestyle factors and ageing", discusses the significance of large datasets in advancing understanding of human cognition and highlights Lumosity, a web-based cognitive training platform, which has amassed over 600 million cognitive training task results from 35 million individuals. This dataset, the largest in human cognitive performance, is part of the Human Cognition Project, a collaborative research initiative by Lumos Labs. The paper presents two preliminary demonstrations using this dataset. The first explores lifestyle factors' correlation with baseline cognitive performance on a larger scale than previously available. The second examines how learning ability for various cognitive tasks changes with age, a question challenging to study at a large scale in traditional laboratory settings. The authors hope these examples inspire researchers to collaborate and address fundamental questions about human cognitive performance.

Manuel Bohn, Johanna Eckert, Daniel Hanus, Benedikt Lugauer, Jana Holtmann and Daniel B. M. Haun, "Great ape cognition is structured by stable cognitive abilities and predicted by developmental conditions", examines the repeatability of cognitive performance in captive great apes (Gorilla gorilla, Pongo abelii, Pan paniscus, Pan troglodytes) across five tasks, aiming to test assumptions about the stability of great ape cognition. The research challenges the notion that cognitive abilities in great apes are solely influenced by experience. Results indicate that task-level performance is generally stable over time, with four out of five tasks being reliable measurement tools. Stable differences in cognitive abilities between individuals were found to be the primary explanation for task performance, and these cognitive abilities were correlated, suggesting shared cognitive processes. The study concludes that great ape cognition is shaped by stable cognitive traits rather than transient experiences.

Fabian Plum, René Bulla, Hendrik K. Beck, Natalie Imirzian, and David Labonte, "replicaAnt : a pipeline for generating annotated images of animals in complex environments using unreal Engine", introduces replicAnt, a configurable pipeline implemented in Unreal Engine 5 and Python, designed to address limitations in deep learning-based computer vision methods for animal behavioral research. The tool generates large and variable training datasets on consumer-grade hardware by placing 3D animal models into procedurally generated environments. This allows for the automatic annotation of images, reducing the need for hand-annotation and enhancing benchmark performance in animal detection, tracking, pose-estimation, and semantic segmentation. Synthetic data generated with replicAnt improves the robustness, subject-specificity, and domain-invariance of trained networks, potentially eliminating the need for hand-annotation in some applications. The tool signifies a significant advancement in bringing deep learning-based computer vision tools to the field of animal behavioral research.

Derek D Reed and Brent A Kaplan, "The Matching Law : A Tutorial for Practitioners", explores the expansion of the matching law from its traditional use as a quantitative measurement tool in experimental behavior analysis to applications in clinical settings. It offers a background on the conceptual foundations of matching, outlines various matching equations used in research, and provides guidance on interpreting data from these equations. The focus is on understanding how naturally occurring events impact socially significant behaviors. The tutorial includes numerous examples of matching analyses conducted with socially important behavior and an appendix directing readers to primary sources and additional resources on the topic.

III. METHODOLOGY

A. Defining research objectives and Data collection

- Collect behavioral data, neurological data and Genetic data based on the requirements of the research.

B. Data cleaning and Preprocessing

- Handling of missing data, duplicate data and Outliers through various methods such as imputation and dropping.

C. Data standardization

- Splitting the data into two categories : Training data and Test data for the model development.

D. Machine learning model selection and model training

- Clustering and Forecast model using algorithms such as K-Means, Prophet, random Forest and Convolution Neural Network.

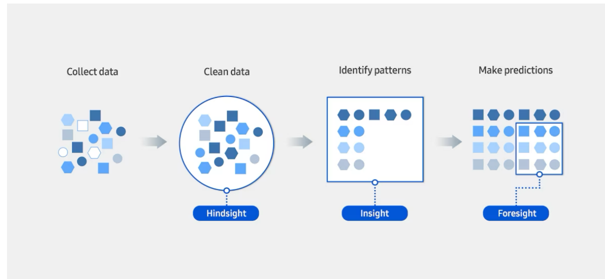

Fig 2 : Illustration of working of predictive analytics

E. Artificial Intelligence for Analysis

- AI techniques, such as natural language processing for textual data and computer vision for image data, to analyze and extract insights from the integrated dataset.

Deep Learning : a significant component in hierarchical feature extraction, employing techniques like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). This proves vital in decoding intricate patterns within complex ethological observations and neuroscientific data, especially challenging for traditional methods. The technology's strength in exploring temporal dynamics enhances insights into evolving animal behaviors over time. Additionally, deep learning's adaptive learning technologies customize educational content based on individual learning styles. It's sophisticated data synthesis capabilities contribute to a nuanced interpretation of complex datasets, providing a comprehensive understanding of cognitive processes across species.

Neural Networks : a tool used in recognizing complex patterns, particularly in decoding animal behaviors. Analyzing ethological observations and neuroscientific data, they offer insights into shared cognitive traits, enhancing our understanding of animal cognition. In time series analyses, neural networks prove instrumental, capturing temporal dynamics in animal behaviors like migration and social interactions. For human cognition, neural networks contribute to adaptive learning technologies, tailoring educational content to individual learning styles. Additionally, they play a vital role in synthesizing findings from diverse sources, ensuring comprehensive integration of insights from ethology, neuroscience, and other disciplines for a holistic understanding of cognitive processes.

IV. EXPERIMENTAL SETUP

A. Data Collection:

- Ape Subjects: Obtain behavioral data from captive ape populations, including interactions, communication, and problem-solving tasks. Collect neurological data through brain imaging techniques and genetic data through non-invasive sampling.
- Human Subjects: Gather diverse cognitive data from human participants, including behavioral assessments, neuroimaging scans, and genetic samples.

Experiment	Task	Publication	WM subsystem	Longitudinal	WM Claim	Comment
Battery of Cognitive Tests	Age for first passing cognitive test	Herrmann et al. (2007), Wobber et al. (2014) (see p. 18 ff.)	SWM, ATM	Yes (synchronic)	Chimpanzees perform less well in the SWM and ATM subsystems than humans and have shorter cognitive development time	Expand linear change in HWM with age to SWM and ATM
Nut Cracking	Tool making and tool usage	Matsuzawa (1994) (see p. 20 ff.)	HWM, SWM	Yes (diachronic & synchronic)	none	Data show HWM = 2 ± 1
Floating Peanut	Innovative solution	Hanus et al. (2011) (see p. 25 ff.)	SWM, ATM	No	Chimpanzees match human cognitive ability of human 7-year-olds	Chimpanzees are comparable to human 3.5-year-olds
Memorize Order of Digits	Digit recall	Kawai and Matsuzawa (2000) (see p. 28 ff.); Inoue and Matsuzawa (2007) (see p. 28 ff.)	HWM	No	Chimpanzee HWM > human HWM	Data show HWM = 2 ± 1 for chimpanzees
Hidden Food	Search for food in closed boxes without repeating any box	Völter et al. (2019) (see p. 30 ff.)	HWM, SWM	No	Chimpanzees have remarkable WM ability	Data show HWM = 2 ± 1 for chimpanzees
Rotating Paddles	Planning ability	Tecwyn et al. (2013) (see p. 46 ff.)	SWM	No	Shows limited planning abilities	Data belie claims about sophisticated planning abilities in chimpanzees
Anticipated Need	Select or make tool in anticipation of future need	Mulcahy and Call (2006) (see p. 47 ff.), Bräuer and Call (2015) (see p.48 ff.)	SWM	No	Act in accordance with future needs	Data show limited ability to make choices in anticipation of future need
Goggles	Follow human gaze as a function of previous experience with goggles	Karg et al. (2015) (see p. 48 ff.)	ATM	No	Ape has level-1 visual perspective taking abilities	Apes failed to follow gaze as a function of their own previous visual experience with goggle-like masks
Transparent versus Opaque Screen	Attribute mental states that one has experienced to others	Kano et al. (2019) (see p. 51 ff.)	ATM	No	Apes take into account the visual perspective of competitor (Theory of Mind)	Modest performance (*circa* 60% success)
Subitizing (Rhesus Monkeys)	Distinguish larger from smaller set of items	Hauser et al. (2000), discussed by Carruthers (2013) (see p. 40 ff.)	HWM	No	Size of subitizing = Size of pure HWM	Size of subitizing is not a measure of pure HWM
Analog Estimator (Chimpanzees)	Distinguish larger from smaller set of items	Beran and Beran (2004) (see p. 41 ff.)	HWM	No	n.a.	Hauser experiment does not measure pure HWM

Fig 3 : Chimpanzee Experiments Relating to Working Memory

B. Data Preprocessing:

- Clean and preprocess collected data to ensure consistency and handle missing values, duplicate values or outliers.

C. Feature Selection:

- Identify relevant features from the integrated dataset that contribute to cognitive outcomes, considering behavioral, neurological, and genetic variables for both apes and humans.

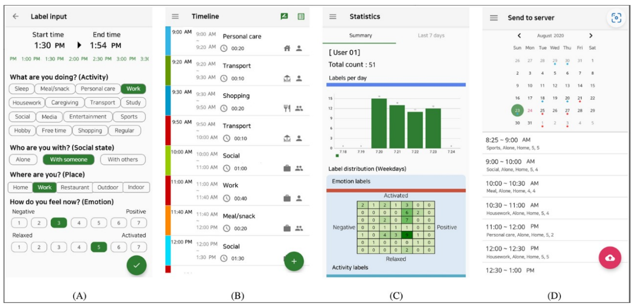

Fig 4 : Life logging application screens. (A) Labeling UI, (B) Timeline, (C) User Statistics, (D) Data upload

D. Deep Learning Model Architecture:

- Implement a deep learning model architecture utilizing Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for hierarchical feature extraction and temporal dynamics exploration.

1. Clustering Model : Clustering segregates data points into groups, minimizing intra-group differences and maximizing inter-group dissimilarities. Employ clustering models like K-Means to categorize and analyze behavioral patterns in both apes and humans, facilitating the identification of common learning strategies within the interdisciplinary research.

2. Forecast Model : Forecast models predict future values based on historical data patterns. Implement forecast models, such as Prophet, to predict future cognitive trends based on historical data, contributing insights into the evolution of animal and human learning strategies.

E. Training and Testing:

- Split the dataset into training and test sets. Train the deep learning model on the training set, adjusting hyperparameters for optimal performance. Test the model on the separate dataset to assess generalization.

1. K-Means Algorithm : K-Means partitions data into k clusters, optimizing centroids to minimize intra-cluster variability. Utilize K-Means algorithm to cluster behavioral data, aiding the project in uncovering shared cognitive traits and learning strategies between apes and humans.

2. Prophet Algorithm : Prophet is a time series forecasting algorithm designed for capturing complex seasonal patterns and

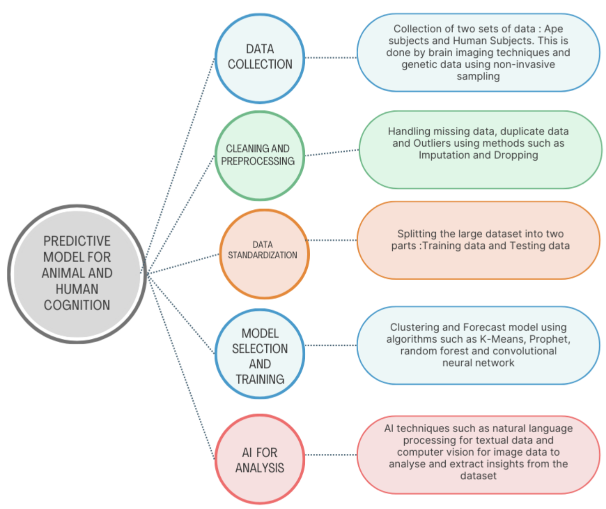

Fig 5 : Delineation of predictive modelling system holiday effects, enhancing accuracy in predicting future values. Apply Prophet algorithm to forecast cognitive behaviors over time, enhancing the project's ability to predict and understand the temporal dynamics of learning strategies in both species.

3. Convolutional Neural Network (CNN) : CNN is a deep learning algorithm, leveraging convolutional layers for feature extraction and pooling layers for spatial hierarchies. Implement CNNs to analyze neuroscientific data, leveraging its pattern recognition capabilities to extract complex features and contributing to the interdisciplinary understanding of cognitive processes in apes and humans.

F. Results Interpretation:

- Collaborate with domain experts to interpret and test results, considering the evolutionary implications and cognitive commonalities identified.

G. Usage of AI for Analysis :

- AI revolutionizes the study of great ape cognition by analysing video footages of apes using AI algorithms, recognizing facial and gestural cues to monitor it's social interaction, and decoding vocalizations in order to help us understand language development, thus, leading to efficient and accurate data collection.

- It enhances cognitive tests, monitors health and habitats, and integrates data for comprehensive understanding. Crucially, AI's predictive modeling capabilities offer insights into the cognitive evolution of apes, deepening our understanding of cognitive development across species, highlighting the interconnectedness of human and ape evolution.

V. RESULTS

The investigation into the evolutionary origin of human cognition from animal cognition yields multifaceted insights across diverse domains. Evidences show that the animal cognition can impact various fields.

Insights from Cognitive Mechanism : By studying the cognitive functions of animals, researchers can identify foundational cognitive mechanisms that are shared across species, including humans. This helps in understanding how complex cognitive abilities, such as memory, attention, and decision-making, have evolved and how they operate in the human brain.

Evolutionary perspective on behavior : Knowledge of the evolutionary origins of human cognition provides an evolutionary perspective on human behavior, including social interactions, communication, and learning processes. It allows researchers to trace the development of these behaviors from simpler forms observed in animals to the complex forms present in humans.

Improvements in Artificial Intelligence : Insights gained from animal cognition can inspire new algorithms and models in artificial intelligence (AI) and machine learning. By understanding how animals solve problems, navigate their environment, and learn, researchers can design AI systems that mimic these natural processes, potentially leading to more efficient and adaptable AI.

Advances in neuroscience : Comparative studies between animal and human cognition can lead to advances in neuroscience. They can highlight specific brain structures and neural circuits that underlie cognitive processes, offering targets for further research and potential interventions for cognitive disorders.

Mental health and neurological health : Comparative cognition research might uncover evolutionary bases for certain mental health and neurological disorders, offering clues about their origins and suggesting new avenues for treatment. By understanding how certain cognitive functions have evolved, researchers may identify why they sometimes go awry in humans.

Personalised learning and cognitive enhancement : Insights into the diversity of cognitive strategies across species can inform the development of personalized learning approaches and cognitive enhancement techniques in humans. Understanding different learning styles and cognitive strengths, as seen across the animal kingdom, may lead to more effective educational tools tailored to individual needs.

The outcome of the study gives the intricate nature of the relationship between human and animal cognition necessitates a nuanced approach for comprehensive understanding. Leveraging predictive modeling to delineate their shared evolutionary traits not only enhances our insight into cognitive capabilities but also exerts a profound influence across diverse fields through its anticipatory power. This research underscores the imperative of delving deeper into the origins and interconnections of cognitive processes, thereby illuminating pathways for future exploration and advancement in our comprehension of the intricacies of cognition.

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