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Original Article

Behavioural Insights through Play - AI and ML Models to Analyze the Transformation of Pet (Dogs) Behaviour with Toys

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Abstract: *Toys are instrumental in exploring the relationship between an animal's behaviour and its surroundings. By watching how pets engage with various toys, researchers can collect valuable insights into their cognitive functions, social interactions, and overall health. This paper explores the application of AI and machine learning (ML) models to analyze how different types of toys influence and transform the behaviour of pet dogs. By leveraging advanced analytical techniques, we aim to uncover patterns in canine interactions with toys, shedding light on their cognitive processes and emotional well-being. The study highlights the potential of AI and ML in providing deeper behavioural insights and improving the quality of life for pets through targeted enrichment strategies.*

Keywords: *AI, Feature distributions, Gradient Boosting, Hyper-parameter tuning, LightGBM, ML, Multilayer Perceptron Regression (MLPR), Normalization, Random Forest, Support Vector Machine (SVM),XGBoost.*

I. INTRODUCTION

Toys are not merely sources of entertainment for dogs; they offer a window into the intricate interplay between a dog's behavior and its environment. The way dogs interact with different types of toys provides valuable insights into their cognitive processes, social dynamics, and over-all well being. These interactions reveal patterns and behaviors that might otherwise go unnoticed, offering a deeper understanding of how dogs perceive and engage with the world around them.

Researchers have long recognized the potential of toys as tools for behavioral studies. By carefully selecting and designing toys that cater to specific canine instincts and preferences, scientists can create controlled environments that elicit natural behaviors. Observing how dogs respond to these stimuli can shed light on their cognitive abilities, emotional states, and social hierarchies.

Moreover, toys can play a crucial role in environmental enrichment, which is essential for the mental and physical health of dogs, especially those in captivity or domestic settings. Enrichment through toys can reduce stress, prevent boredom, and promote natural behaviors, ultimately enhancing the quality of life for pet dogs. By studying the impact of different types of toys on dog behavior, researchers can develop more effective enrichment strategies that cater to the specific needs of different breeds and individual dogs.

The insights gained from observing dogs at play extend beyond academic research. Pet owners and caregivers can also benefit from understanding how toys influence behavior. For instance, identifying toys that promote positive interactions can strengthen the bond between dogs and their owners. Additionally, toys that encourage physical activity can help prevent obesity and related health issues in dogs, contributing to their overall well-being.

II. APPLYING AI AND ML TO ANALYZE PET BEHAVIOUR

Recent advancements in artificial intelligence (AI) and machine learning (ML) have revolutionized the field of animal behaviour analysis. These cutting-edge techniques, collectively known as Computational Animal Behaviour Analysis, enable researchers to capture and quantify intricate behavioural patterns that were once challenging to measure. By leveraging AI and ML, scientists can now gain deeper insights into the cognitive processes, emotional states, and social dynamics of animals. Traditional methods of observing and analyzing animal behaviour often rely on manual recordings and subjective interpretations, which can be time-consuming and prone to human error. AI and ML models, however, bring a new level of precision and efficiency to the table. By processing large volumes of data collected from sensors, cameras, and wearable devices, these models can identify and quantify subtle behaviours that might be overlooked by human observers.

Recent studies have highlighted the potential of applying AI and machine learning techniques to the analysis of animal behaviour. These approaches, collectively known as Computational Animal Behaviour Analysis, have demonstrated the ability to capture and quantify subtle behavioural patterns that were previously difficult to measure. This study in this paper utilizes advanced machine learning algorithms including XGBoost, Random Forest, Support Vector Machine (SVM), Gradient Boosting, Multilayer Perceptron Regression (MLPR), and LightGBM to explore how the type of toy, including its size, colour, and other variables, can significantly impact a pet's behaviour and preferences, influencing their engagement, cognitive stimulation, and overall well-being.

III. METHODOLOGY

Data Collection: The dataset for this analysis is generated based on a hypothetical scenario involving dogs and their interactions with various toys. The data includes a wide range of variables to simulate real-world conditions. The dog-related attributes include breed, age, size (small, medium, large), energy level (low, medium, high), weight, gender, health condition (healthy, minor issues, chronic issues), training level (none, basic, advanced), and anxiety level (low, medium, high). For the toys, the information includes toy type (ball, chew toy, plush, etc.), material (rubber, fabric, plastic, etc.), size (small, medium, large), durability (low, medium, high), colour, squeaky (yes/no), and toy brand. Interaction data encompasses frequency of play (times per day/week), duration of play (minutes per session), dog's interest level (low, medium, high), favourite play time (morning, afternoon, evening), and calmness after play (low, medium, high).

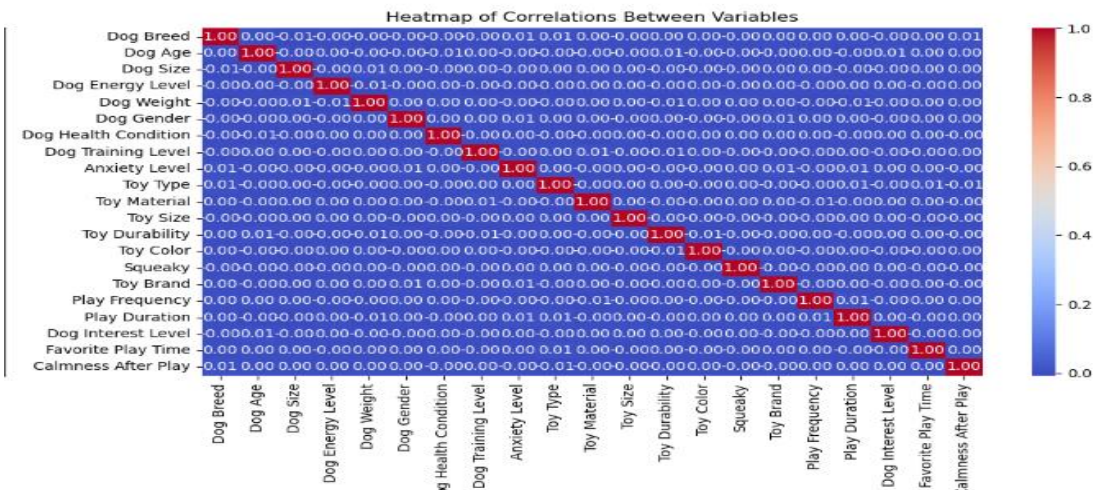

Figure 1: Heat-map of Correlations

IV. REGRESSION MODELS

- *XGBoost:* Extreme Gradient Boosting is a machine learning algorithm that excels in both classification and regression tasks due to its high performance and efficiency.
- Attained F1 Score: 61%
- *Random Forest:* Is an ensemble learning method that builds multiple decision trees and merges their predictions to improve accuracy and avoid over fitting. It works well for both classification and regression tasks by averaging the results of individual trees to make robust predictions. Attained F1 Score: 64%
- *Support Vector Machine (SVM):* SVM is a supervised learning algorithm that finds the optimal hyper plane to separate different classes in the feature space. It is effective for both classification and regression tasks, especially in high-dimensional spaces and for cases where the decision boundary is non-linear. Attained F1 Score: 58%
- *Gradient Boosting:* is an ensemble technique that builds models sequentially, each one correcting the errors of its predecessor by minimizing the loss function. It combines the outputs of these weak learners to produce a strong predictive model, excelling in both classification and regression tasks. Attained F1 Score: 61%
- *Multilayer Perceptron Regression (MLPR):* MLPR is a type of neural network that uses multiple layers of neurons to model complex relationships between inputs and outputs. It excels at capturing non-linear dependencies in data, making it suitable for both regression and classification tasks. Attained F1 Score: 66%
- *LightGBM:* Light Gradient Boosting Machine is a fast, efficient, and scalable implementation of gradient boosting that uses histogram-based algorithms to speed up training and improve memory usage. It performs exceptionally well with large datasets and complex models, making it ideal for both classification and regression tasks. Attained F1 Score: 64%

V. OBSERVATIONS

Initially, the model exhibited only 38% accuracy when trained on the raw dataset, indicating limitations in data quality and feature representation. To enhance performance and ensure robust predictions, several data pre-processing techniques were applied. These included hyper-parameter tuning to optimize model parameters, normalization to standardize feature distributions, and a structured training-test split to prevent over-fitting.

Additionally, optimization techniques were implemented to refine the learning process, and the dataset was expanded to improve sample diversity and overall generalization. These refinements led to a significant improvement in model accuracy R square boosted it to 66%. Further improvements, such as more trained and test data sets, feature engineering and the integration of additional behavioural factors, could further refine the model's accuracy and reliability.

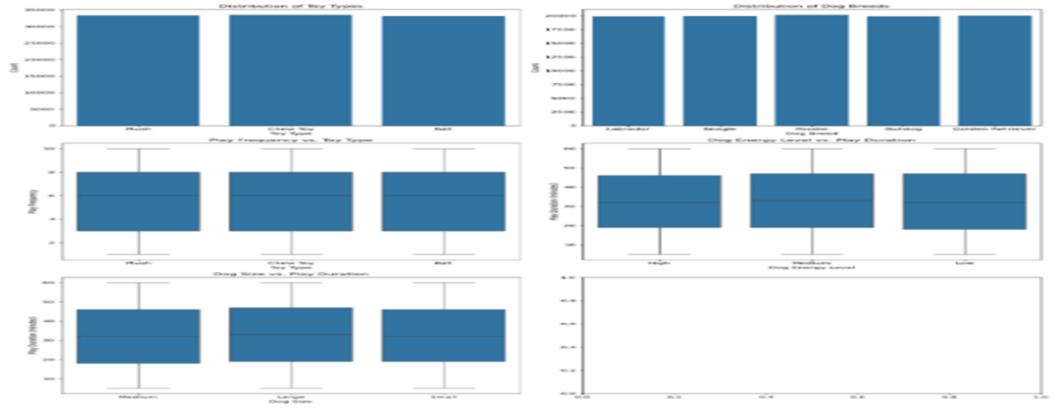

Figure 2: Data Distribution

A. Key Takeaways:

- Age directly affects **both engagement and relaxation post-play,** with younger dogs requiring more physical activity and older dogs benefiting from mentally stimulating toys.
- Toy selection significantly impacts **behavioural responses and calmness,** highlighting the need for personalized toy choices for different dog breeds and energy levels.
- Further refinements in model training could improve predictive accuracy and deepen insights into pet behavior

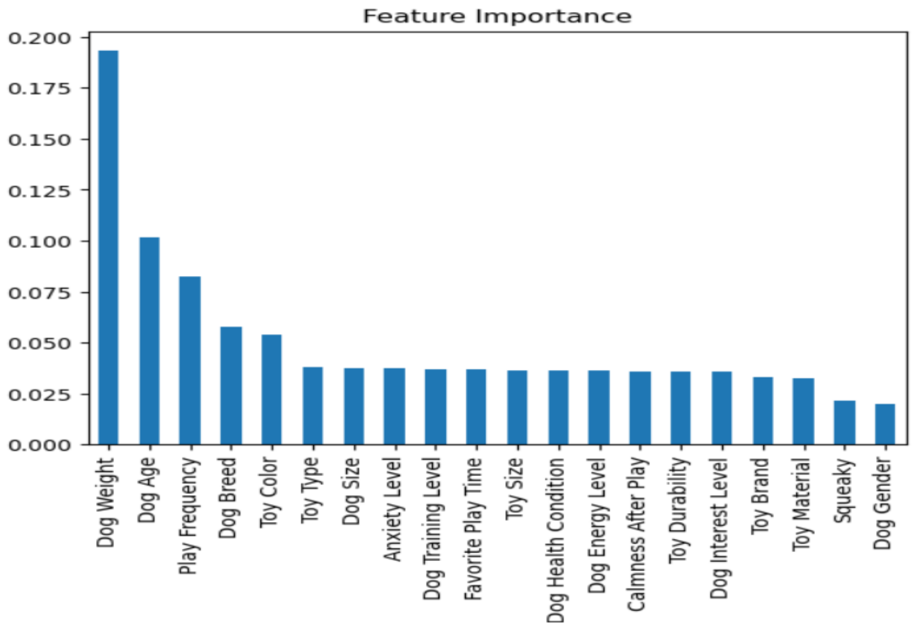

Figure3: Feature Importance

VI. CONCLUSION

The application of AI and ML models to the analysis of pet behaviour through toys will yield promising results, providing a more comprehensive and objective understanding of the complex interplay between an animal's behaviour and its environment. The results of this study demonstrate the potential of combining advanced AI and ML models with the analysis of pet-toy interactions to gain comprehensive and objective insights into pet behaviour.

Future Study: Further research is needed to enhance accuracy and expand insights. Future work should focus on integrating **real-time datasets** collected from sensors, cameras, and wearable devices to capture more dynamic behavioural patterns. Additionally, incorporating **a wider range of variables** could improve predictive accuracy. More extensive training on diverse datasets will help refine models, enabling deeper behavioural insights and achieving an **accuracy exceeding 90%.** Advanced analytics, including ensemble learning and reinforcement learning techniques, can further optimize predictions and provide personalized recommendations for pet enrichment strategies.

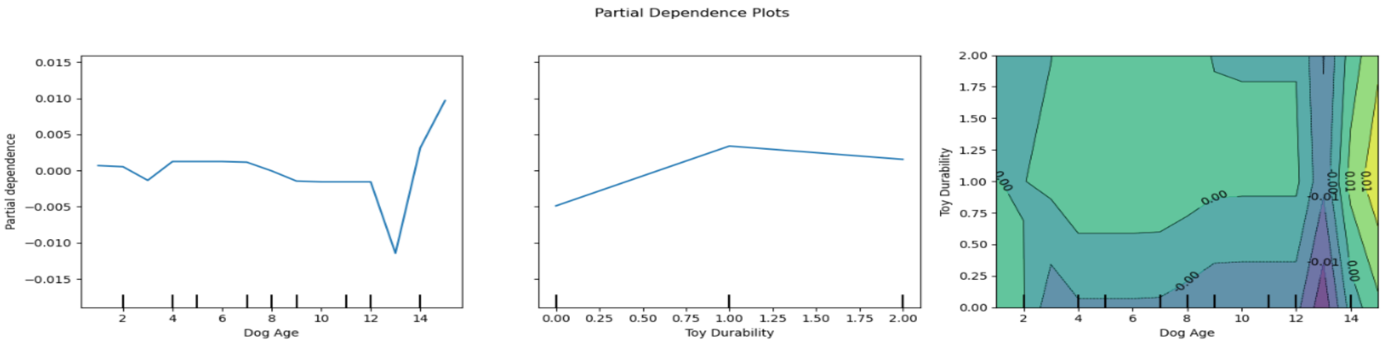

Figure3: Feature study

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