Neural Network-Based Analysis of a Supersymmetric Model Contribution to the Muon (g-2) Anomaly (Abstract)

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In this work, we aim to analyze the well-known anomaly in the muon's magnetic moment from a different perspective. The discrepancy between the theoretical and experimental values stands at 5.15σ. To address this, we employ a flavor-extended Minimal Supersymmetric Standard Model (MSSM) that includes a hierarchical family structure in the trilinear scalar soft-supersymmetric terms of the Lagrangian, defined at the Supersymmetry (SUSY) breaking scale. This framework introduces five free coupling parameters within specific ranges. We propose to reduce the discrepancy between theory and experiment to the range $[3.15\sigma, 4.15\sigma]$. Using Neural Networks (NN), we predict the supersymmetric contribution a_μ^{SUSY} and examine the influence of each parameter.

We perform this optimization by generating random distributions for the five SUSY parameters and selecting those that yield the reduced deviation range, i.e., $a_\mu^{\mathrm{SUSY}} \in [3.15\sigma, 4.15\sigma]$. These selected parameter sets are then used as input for our Neural Network, while the corresponding a_μ^{SUSY} values, explicitly computed from the SUSY model, are used as target outputs for training.

We verified the optimal configuration and distribution by evaluating the model using appropriate performance metrics until accurate predictions were achieved. The final analysis of the trained model revealed how the neural network weights were assigned to each of the five input parameters. This examination uncovered a strong relationship between certain coupling constants and their corresponding probability distributions, particularly highlighting a pair of parameters that are inherently coupled by definition.

The goal of this work is to provide an alternative approach to obtaining phenomenological predictions—such as observables and theoretical contributions—while avoiding the computational burden of traditional analytical methods. Once trained, the model can directly predict the SUSY contribution given a specific set of input parameters, serving as a fast alternative to traditional analytical computations.

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