An Evolutionary Partitioning Approach for an Ensemble Classifier

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INTRO

➤ An evolutionary algorithm (EA) is a computational algorithm inspired by principles from biological evolution.[1]
➤ Our approach incorporates genetic mutations and a “survival of the fittest” pruning method to assist in a classification task.[2]
➤ Our method aims to analyze smaller domains of a dataset using an evolutionary approach to evolve hyperspherical receptive fields that can perform classification based on smaller subsets of the data.

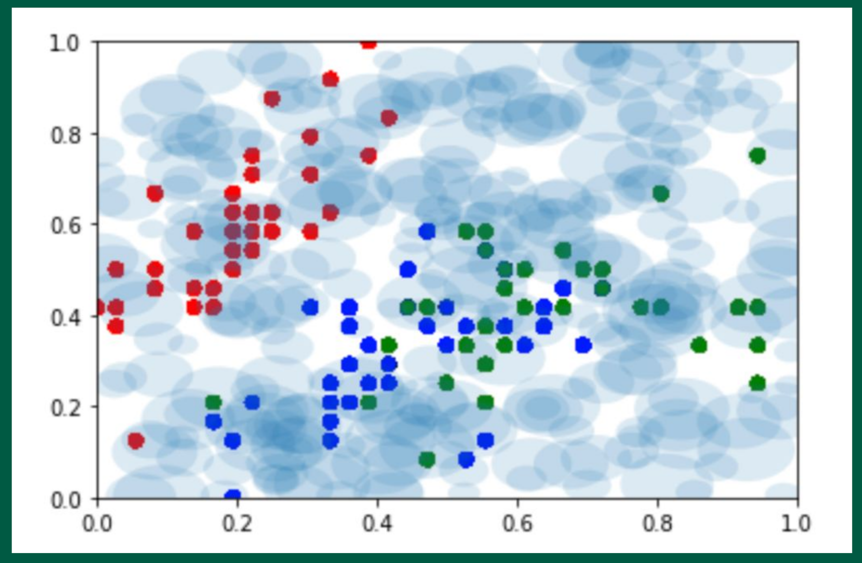
METHODS

Dataset:
➤ The iris dataset is a widely-used dataset in the field of machine learning. It contains of 150 examples of flowers with 4 features (i.e., sepal length, sepal width, petal length, and petal width), and 3 classes of the iris flower (i.e., Iris Setosa, Iris Versicolour, and Iris Virginica).

Procedural Implementation:
➤ We initialize a random population of a set of N-different sized hyperspheres throughout the dataset
➤ In each sphere, we train a support-vector machine classifier on any contained data points.
➤ We evolve our population according to top performing survivor spheres from the last generation, mutations of these top scorers, as well as new random spheres to maintain population density.

Abstract: Multi-class classification algorithms such as SVMs and KNNs can sometimes fail to capture patterns within smaller subspaces of the dataset. Our approach aims to partition domains of the dataset using evolving spherical receptive fields that performs nonlinear classification. We implement a genetic algorithm to introduce stochastic mutations, cross reproduction, and population pruning of the receptive fields through a fitness function and evaluate the performance of the population. The resulting spheres of the last generation collectively comprise the optimized ensemble classifier.

Findings: The evolutionary algorithm uncovered a straightforward strategy for optimal survival, demonstrating a phenomenon of cluster convergence.



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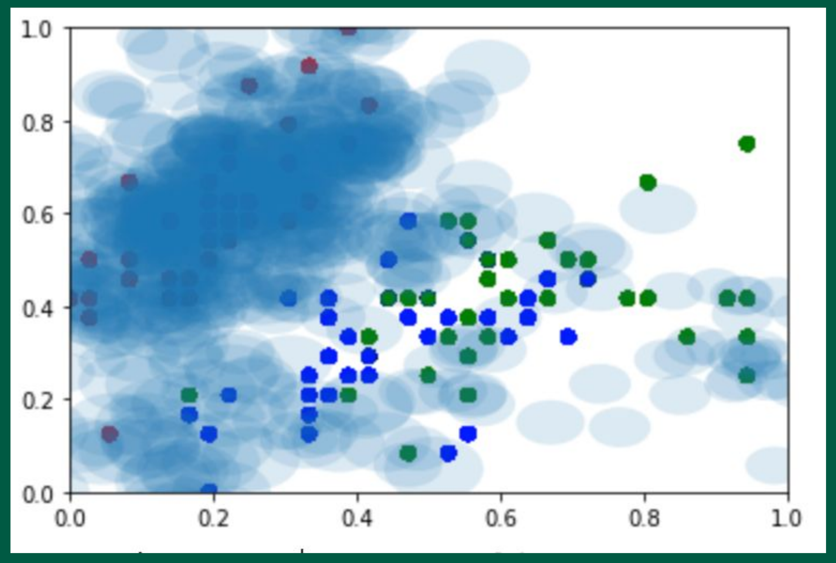

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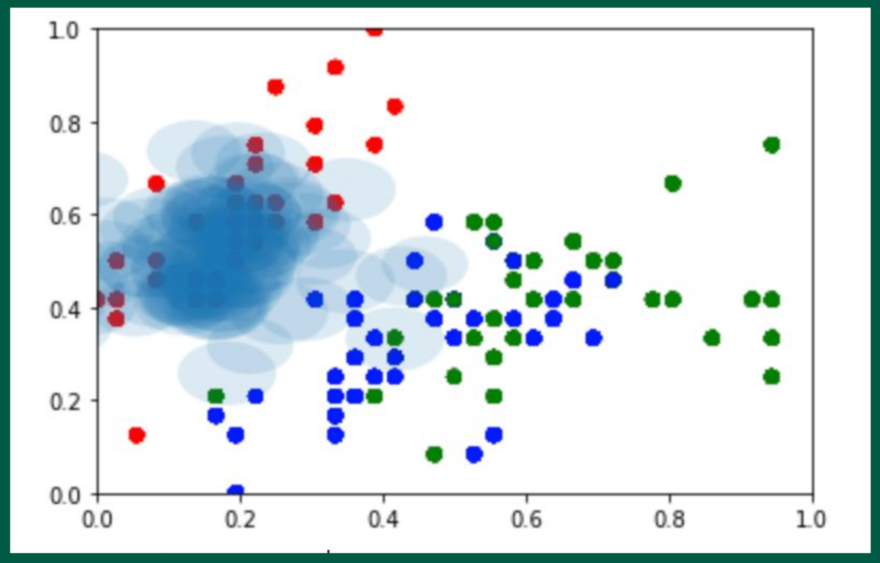

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RESULTS

➤ The spheres eventually found that clustering around an “easy” region of space containing only one class, which maximized its chances of survival and thus, led the population to converge only around one area because of the simple categorization.

DISCUSSION

➤ Simplicity and efficiency seemed to be the dominating factor that allowed our population of spheres to evolve. Given the goal of survival, our population took the simplest path to “success” and found a way to “cheat” the system.
➤ Optimization tuning is extremely important, we must find new efficient ways to explore a range of different hyper-parameters.
➤ One approach is to implement certain constraints in our algorithm. Biological evolution in the real world would not exist without nature’s constraints. This same logic can be applied to our evolutionary based algorithm, where we can introduce certain constraints in our algorithm to mimic natural limitations of the fundamental laws of nature.

REFERENCES

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