Chemical Reaction Optimization Using Artificial Neural Networks for Predicting Stock Market Indices

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***Abstract*—** The academic fields of computational statistics and financial mathematics have used stock index predictions as a benchmark for several decades. For the purpose of making reliable forecasts of stock prices, several distinct machine learning algorithms have been created. In this research, we use a hybrid model that incorporates both traditional CRO techniques and an ANN to predict the BS E's indices. To get a good start on our CROs, we employed the UP method to establish a large pool. The preprocessed data used for training and testing includes the daily closing prices on the BSE. The model's prediction accuracy is measured against that of a multilayer perceptron (MLP) model using the Average Percentage of Errors (APE) metric. Following this rationale, it appears that the ANN-CRO model could be a useful tool for predicting market indices.

Keywords: Chemical Reaction Optimization (CRO); Artificial Neural Network (ANN); Multilayer Perceptron (MLP).

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I. INTRODUCTION

To illustrate the average movement of stock prices, the stock market uses an index. It is not indicative of the price movement of a single stock but rather of the market as a whole. The high volatility of the market, non-linearity, the complexity of the dynamic system, and the fact that it varies over time all contribute to the difficulty of accurately predicting stock indexes. If one wants to develop smart methods for forecasting stock market indices, it is crucial to incorporate these problems into the models that are actually used and put into effect. These are the models that are really utilized and implemented. Predicting the stock market's action reliably involves doing so with as little hassle and complexity as possible. Researchers in the stock market try to improve methods for anticipating stock index values so that investors can make the most money possible trading strategies, a crucial yet difficult topic in the field of financial mathematics. Many computational and traditional models have been developed during the past two decades to deduce the underlying patterns in real-world stock index data, which is an issue that actually exists. Using a more conventional network architecture and tried-and-true optimization techniques, we develop an artificial neural network (ANN) model to foretell the index's future value. We call our optimization strategy for the network's connective weights and other parameters ANN-CRO, after the chemical reaction that inspired it. To accomplish this, we develop a model using an ANN.

The remainder of the paper is structured as follows. The second part is some descriptive exploration that we can peruse. In Section III, we will demonstrate how we collected and cleaned the data utilized in the next sections. The evolution of the synthetic chemical reaction was discussed in this series' final chapter. V expands on what we know about CRO's practical uses. After a brief summary of the general results, Section VI provides a detailed analysis of the experiment's results.

II. RELATED WORK

Artificial intelligence (AI) methods like ANN, fuzzy logic, and GA have long been used in the financial and trading systems. The use of ANNs has grown increasingly common in this setting. The results of the studies show that ANN is not ideal for making stock predictions. Acquiring an adequate quantity of training data and tweaking the network's parameters fall under this heading. The optimal duration of training data needs to be determined. By estimating the rate of change in closing price on the test for 36 businesses trading on the NYSE and NASDAG, the authors of [2] enhanced the buy-and-hold strategy (BHS). Some studies [3, 4] modelled the connection between stock trading signals and effect components using a back-propagation neural network. ANNs can get caught in a local minimum or over-fit, both of which are problems. Twenty companies listed on the Shanghai Stock Exchange in China were analyzed using a model developed by L. Luo and Xi Chen that integrated piecewise linear representation and weighted support vector machine (PLR-WSVM). PLR-WSVM has been shown to be more accurate and profitable when making predictions than PLR-BPN and (BHS) [5]. Standard ANN model MLP has been shown to perform marginally better than dynamic artificial neural network (DAN2) and generalized autoregressive conditional heteroscedasticity (GARCH-M LP) in recent studies [6].

III. COLLECTION AND PRELIMINARY PROCESSING OF DATA

Every day, the closing prices from the Bombay Stock Exchange (BSE) are compiled using data from the BSE's official website [7]. There are, on average, 256 closing values each year in the data set. Preprocessing often makes use of transformation and normalization. Before being fed into a learning system, data must be normalized to ensure they are of appropriate quality. The neural network can be used to standardize the data so that all of the input features can take on the same values. If the neural

network contains any bias, this will help to eliminate it. By starting the process for each feature on the same scale, data normalization can reduce the total time spent training. For modelling applications where the inputs typically span multiple scales, this is a huge help. The daily closing price data used in this experiment has been normalized using decimal scaling normalization. To change the values of property A, the decimal point is shifted as high as it may go. The number of modified decimal places is determined by the maximum absolute value in data set A.

IV. OPTIMISATION OF CHEMICAL REACTIONS

The concept of optimization is essential to both the theoretical and practical branches of research. Most problems can be thought of as optimizations, including the scheduling of power generation in electrical engineering [8], the sequencing of DNA in medicine [9], and the predicting of market movements in finance [10]. Chemical Reaction Optimization (CRO) is an emerging meta-heuristic for optimization that draws inspiration from the kinetics of chemical reactions. Chemical reactions include the transformation of reactive substances into those with greater stability. Chemical reactions require unstable, high-energy molecules as catalysts. The enthalpy of a chemical system is a measurement of its total energy. Simple chemical reactions between the molecules lead to several intermediate chemical compounds. The optimal shape is the one with the lowest enthalpy need for its continued existence. CRO includes this function for fixing optimization problems. Optimization strategies that mimic natural processes have advanced rapidly during the past few decades. Most commonly, these algorithms are population-based and can be used to solve a wide variety of issues. Just what it is Many academic fields rely heavily on the ability to optimize systems [8-10]. In the context of optimizing chemical reactions, "CRO" stands for a novel meta-heuristic tool. The dynamic nature of chemical reactions inspired the creation of this term. Reactive chemicals are transformed into more stable ones by chemical reactions, which occur naturally. An effective catalyst for a chemical reaction must be an energetic and unstable molecule. Enthalpy is a thermodynamic quantity used to quantify the energy content of a chemical system. Simple reactions driven by molecule-on-molecule interactions produce some of the intermediate chemical substances. They evolve into shapes that allow them to stay alive while expending the least amount of enthalpy (energy). Including this feature in CRO helps fix issues connected to optimization. Advances have been made in the development of optimization systems that mimic natural processes. These algorithms can be easily modified to fit a wide range of problems, and they usually make use of demographic information to do so. The term "evolutionary algorithm" was developed since many artificial intelligence programmes are built to mimic the way nature operates. The "evolutionary algorithms" class of computer programmes simulates natural processes by gradually evolving a set of options. Examples of such algorithms include genetic algorithms, ant colony optimization, particle swarm optimization, differential evolution, and hybrid search (HS). Their operational scales range from the genetic (GA, MA, and DE) to the organismic (ACO and PSO), all of which are based on biological processes. HS is driven by the human part of music production, while the other two are motivated by various things. All sorts of optimization problems have optimal solutions that can be found using these techniques. A novel meta-heuristic for optimization [11] was recently presented by Lam and Li, and it takes cues from the speed with which chemical reactions take place. The full meaning of CRO is "chemical reaction optimization," which is why it is commonly abbreviated to "CRO." CRO has been successfully implemented in a wide range of situations in a short amount of time, and most experimental findings have demonstrated its superiority to alternative evolutionary algorithms. Because of this, it has becoming increasingly popular for use in quick fixes. CRO has been shown to be effective in multiple-sequence alignment, data mining, and classification rule building, among other benchmark functions [12, 13]. This is happening in an increasing but still relatively low number of instances.

V. CRO'S USE IN PREDICTING STOCK MARKET INDICES

A chemical transformation takes place whenever two different chemicals are brought together. As a consequence of carrying out this process, several products derived from the reactants will emerge. There is the possibility that N distinct molecules or reactants will be involved in each of the M possible chemical reactions. There are a variety of answers that can be executed in the opposite order. When a chemical system is getting close to reaching equilibrium, the rate at which it is reacting forward is equal to the rate at which it is reacting backward, and the other measured properties and concentrations do not change. After that period of time, the answer will no longer be useful.

The ACROA process kicks off with the introduction of a number of reactants into a solution. Following that, the reactants are consumed by the chemical processes, which ultimately result in the formation of the products. In the same way that a chemical reaction is complete after an inert solution has been produced, the procedure is finished once the final condition of the algorithm has been satisfied.

where E(n) represents the overall error that is incorporated into the index forecast due to the inclusion of all reactants. Here are some of the results that would be ideal! In this situation, lowering the error function produces an impact that is analogous to that achieved by reducing the enthalpy of a chemical reaction. The reactant that contributes the least amount of enthalpy to the processes that are still going on is a suitable candidate for elimination. It's probable that the case will need to be cracked using a combination of several encoding methods, such as binary, real, permutation, and others. In the course of this experimental research, binary encoding was looked into as a potential method of data storage.

A. Setting the initial reactants and evaluation

The full viable searching region is then given initial doses of the reactants that are consistent across the board. The method of uniform population [14, 15] was utilised in order to construct the beginning populations that were utilized in the production of the starting reactants for this experiment. A set of vectors can be formed in the majority of situations by merely multiplying the vectors' component components by a linear factor that is shared among them. If the missing member of the base set corresponds to the dimension in question, then the dimension in question is functionally nonexistent. As a result, the initial reactants have to comprise reactants that are able to maintain each individual member of the base set. In order for the beginning reactants to be valid, they need to meet both the regularity case criteria as well as the base set condition. Every individual in the population stands for a unique value of the variable being studied. These parameters can be things like the weights that connect the input layer to the hidden layer or the bias values that those layers employ. Some examples of these settings are shown below. The reactant representation of the ANN-CRO model is displayed in Figure 1. These are the bias values for the hidden layer, which has n hidden nodes and m inputs. The hidden layer has a total of m inputs. Take a look at the value B0 to get an understanding of the bias that the output layer has. There are a total of eight binary digits that are utilised in order to signify the to, to, and bias values contained within each cell. The decimal representation of the binary reactant is used in the calculation of a neuron's weighted sum in both the hidden and output layers.

B. Making use of chemical processes

1) Synthetic Process

It is possible to pinpoint the components of two reactants that are at odds. Then, a new reactant is made by selecting, in order, one bit from the first reactant's non-matching bit and one bit from the second reactant's non-matching bit. The resulting reaction is shown in Figure 1.

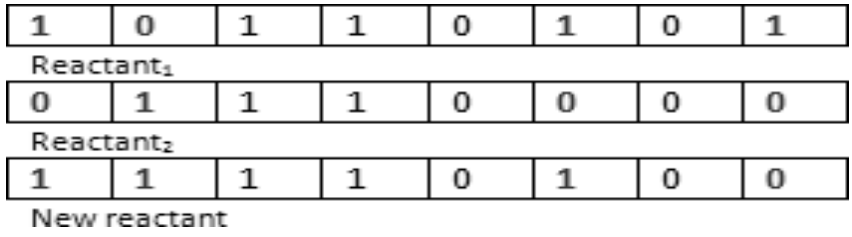

Fig 1. Encoding into binary using a synthesis process

2) Displacement reaction

A mask that is analogous to the one utilized in genetic algorithms for the process of uniform crossover is generated at random in order to assist in the determination of whether or not two strings of bits are able to transmit information with one another. If the mask value for the suitable bit location in the string is 1, then the bits of the reactants are not swapped because doing so is not necessary given the current state of the situation. On the other hand, if it is a 0, the bits that are now in those locations will be swapped. The binary version of this reaction is displayed for your convenience in Figure 2, which may be found here.

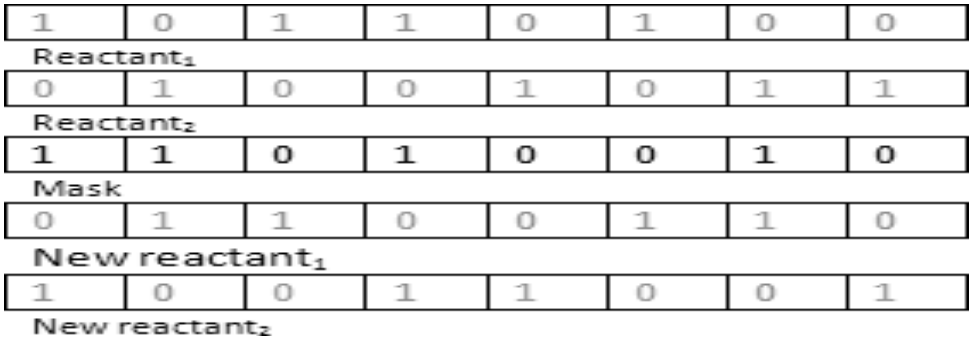

Fig 2. Binary encoding's displacement reaction

a) Redox2 reaction

To swap out pieces of the reactants at two arbitrary locations, we utilize a 2-point crossover, similar to that used in genetic algorithms. The redox2 reaction is depicted in Fig. 3.

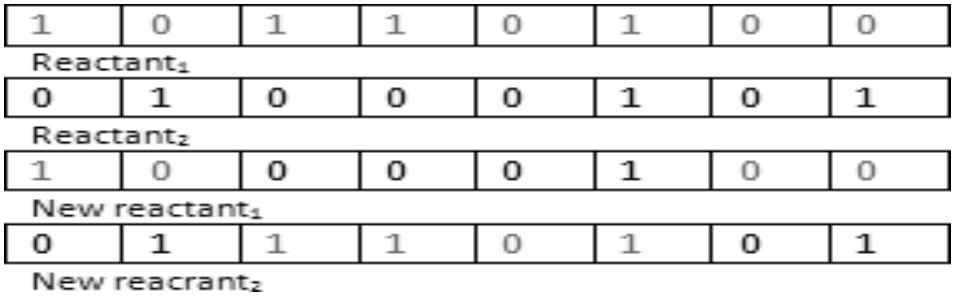

Fig 3. Binary encoding through redox2 reaction

b) Reaction of decomposition

The bits of the reactant string are swapped in two different locations: one comes before, and the other comes after. The outcome of this activity is depicted in Figure 4.

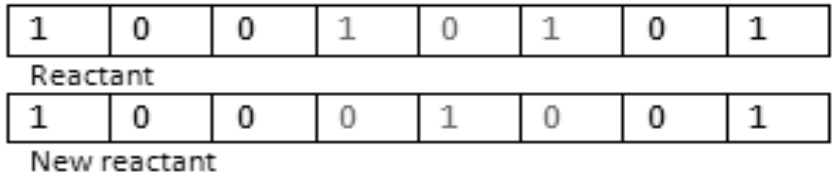

Fig 4. Binary encoding decomposition reaction

c) The Redox1 Reaction

A bit is arbitrarily set to either one or zero. The redox1 reaction's binary depiction is shown in Fig. 5.

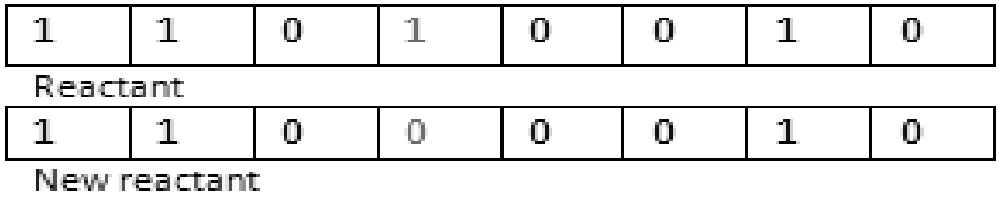

Fig 5. Binary encoding through a redox1 reaction

d) Update on Reagents

A test for chemical balance is being carried out right now. Similar to how reversible chemical reactions work, if the newly formed reactants provide a higher value for the function, then the set of newly created reactants is included in the reaction and the less desirable reactant is removed from the reaction.

e) Verification of Ending Criteria

When the termination condition, which might be the maximum number of iterations that can be reached or the least enthalpy value that can be obtained, is satisfied, the CRO Algorithm is complete. The termination criterion could be one of these things. In this particular scenario, the steps C and D from the prior algorithm are repeated. The following illustration provides a representation of the CRO pseudo code.

VI. RESULTS AND DISCUSSION OF THE EXPERIMENTS

The evaluation was done on a machine that featured a 2.27 GHz Intel Core i3 processor and 2.42 GB of RAM. MATLAB-2009 Version 7.8.0.347 was used for the analysis in this paper.

The network's output is the S&P100 index price at the end of each trading day, and it was trained using data containing the BSE indexes' historical values [7]. These specifics were utilized by the network. The index values cover a time period of seven years, from 2005 to 2011. It is possible to construct a financial time series using the day's final pricing. In order to standardize the data, it is first transformed to the decimal system. From the normalized data, a training bed for the network model may be built. Using the sliding window method, in which N inputs and 1 output are shifted across the whole

time series, we studied this set of economic data. The input vectors X1, X2,..., XN are built from the time series x1, x2,..., xt-1, xt, while X2 is built from x3, x4,..., xN+1, and so on. One input vector and one target value make up a training sample in machine learning. The input layer neurons receive the input vector, while the output layer neuron receives the target. With "error" referring to the difference between the observed and predicted results, both the weights and the bias values were updated to reflect the most recent data. Error values above a certain threshold cause the training phase to end and the following record to be utilized for validation. The percentage of average absolute error represents a performance metric. This sentence sums up the blunder in the e-i data pattern:

$$e_i=abs(t_i-y_i)----------1$$

Here, we have the deviation from the signal that was planned (), the signal that was desired (), and the output that actually occurred (yi). After repeating the model simulation ten times, we gathered the data needed for our study and factored in the average error. The model of a feed-forward neural network that was investigated only contains one hidden layer. The MLP model's internal structure is illustrated in figure 7, which may be found here. Within the scope of this architecture, there is just a single output module. Although the transfer function of the neurons in the input layer are linear, the transfer function of the neurons in the hidden layer and the output layer are sigmoidal.

$$Y_{out}=1/1+e^{-yin----------2}$$

Figure 6 provides a representation of the structure of the ANN-CRO model. This model makes use of a network that is very much like the MLP network that is shown in Figure 7, but it only has one hidden layer. The reactants in CRO are a symbolic representation of the weight and bias parameters used in numerous different MLP models. The input data for the MLP models are daily closing prices that have been normalised and reactant values that have been reported as decimals. The enthalpy (E) for the weight and bias set is calculated by taking the absolute difference between the desired output and the estimated output. This value is then used to establish the fitness level. If the enthalpies of each of the reactants are lower, then the CRO believes that the reaction will go more smoothly. The production of the CRO's seed population utilises a method known as "uniform population," as described in detail in [14, 15].

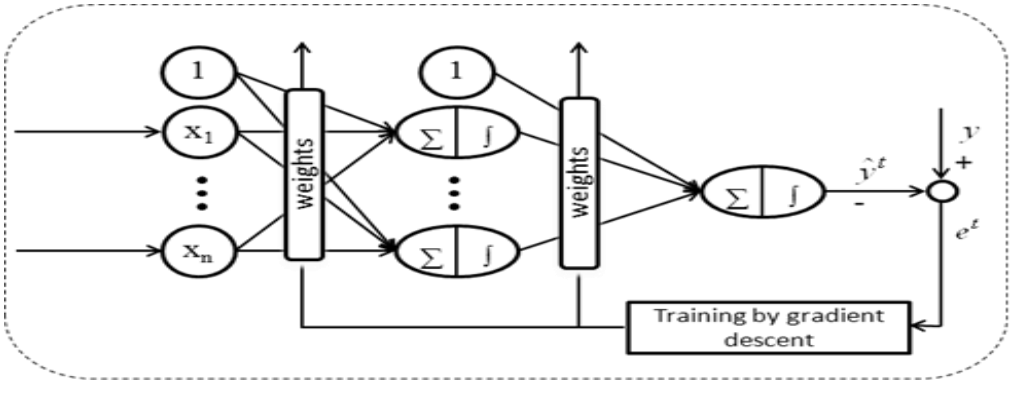

Fig 6 . The MLP Architecture

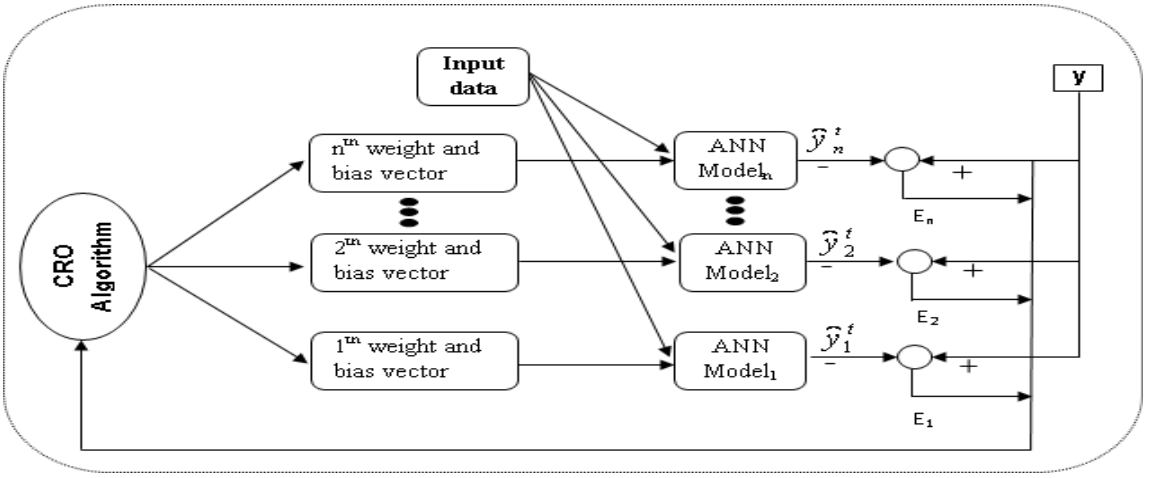

Fig 7. The ANN-CRO Architecture

Table 1: Combined Standard Error Rate Of The Two Forecasting Methods

Financial Year	Average Percentage of Error (APE)	
	ANN-CRO	MLP
2005	0.0822	0.1172
2006	1.3716	1.5464
2007	0.2359	0.4263
2008	0.9905	0.5126
2009	0.9922	1.8861
2010	0.9460	1.8674
2011	1.6083	1.3179

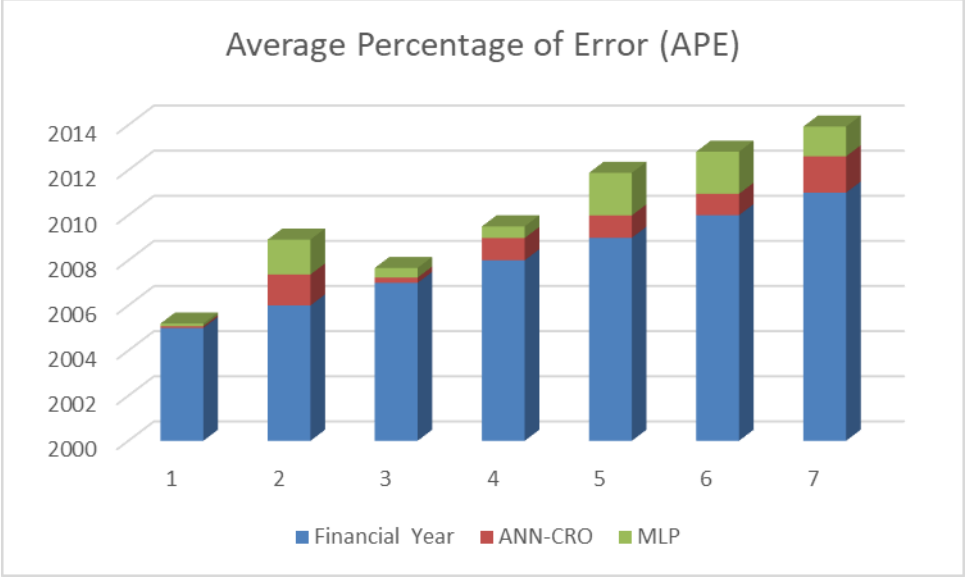

Fig 8. Comparison of MLP & ANN-CRO Prediction Accuracy in Terms of the Mean Percentage of Mispredictions

Experiments were conducted using both models, and the results are detailed in Table I, which may be found below. The results of a comparison of their skills are shown in Figure 9. The ANN-CRO model exhibited a far larger degree of accurate prediction in comparison to the MLP model, with the exception of the years 2008 and 2011.

VII.CONCLUSION

Hybrid models, which combine elements from other models, have gained popularity over the past few decades as a way to boost prediction precision. Multiple experiments are often conducted to define the optimal design of ANNs, which includes discovering the optimal relevant feature subset and the ideal parameter set. It is obvious that a lot of time is required for this process. This allows a chemically motivated method, such as CRO to be used to determine the optimal parameter configuration. Both the training parameters and the weight sets used in this research were optimized with the help of CRO. These real-world examples show how the hybridized system may be a useful tool for predicting stock market trends and prices. By contrasting the hybrid model's predictive skills with those of a more standard MLP model, we conclude that the latter is the more promising option. By contrasting the ANN-CRO model and the MLP model, we may better understand the strengths and weaknesses of each.

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