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ATM Forecasting using Optimized Artificial Neural Networks

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Abstract: Running out of money at an ATM or other place results in higher costs for unscheduled currency supplies and less income from lost surcharge fees. However, banks are unable to invest this non-earning assets to produce interest revenue due to oversupply of currency. ATM forecasting automation is therefore urgently needed. Artificial neural networks are utilized as a forecasting method in this study because they function well for automated prediction tasks. The most significant algorithm for neural network training is propagation in reverse. However, it is prone to become stuck in local minima, which might result in incorrect answers. Thereby, in order to hybridize with artificial neural networks, a few global search and optimization strategies were needed. Genetic algorithms that mimic the idea of natural growth are one such method. Therefore, a hybrid intelligent system that combines genetic algorithms and neural networks made up of neurons is presented for ATM forecasting in this study. The suggested mixed approach functioned better than the current back propagation-based system, according to the results.
Keywords: ATM forecasting; cash prediction; artificial neural networks; Genetic algorithms; Hybrid intelligent system; forecasting.

I. INTRODUCTION

ATM forecasting is the capacity to project future cash requirements for automated teller machines (ATMs). Making ensuring that cash is spent properly and efficiently across the branch network is the main goal of ATM forecasting [6] [8]. In the ATM network services industry, one of the most crucial aspects is ATM forecasting and service accessibility. By optimizing ATM expenditures and effectively routing cash loads, banks can prevent cash-stuck ATMs and effectively manage the system in an ever-shifting environment while meeting the various needs of ATM network users. More banks are currently focusing on finding ways to handle their cash at ATMs more efficiently [10].

Capturing and analyzing previous data to yield future insights is essential to the ATM's predictive algorithms.[1] Recently, several writers have tried to estimate and forecast the demand in order to maximize the cash [11]. Nonetheless, the dependability of these methods may be impacted by the underlying stochastic cash demand process's high volatility and non-stationarity. In addition, the demand for cash is not only impacted by time but also exhibits various trends that exacerbate the difficulty of predicting. For instance, weekends, holidays, the beginning of the month, festival days, etc. [2] [9]. Hence, the task of ATM forecasting can be well resolved by effective artificial intelligent forecasting algorithm for accelerating the issues of slow training and optimal solution discovery, such as artificial neural networks combined with some optimization techniques like genetic algorithms. [21]

The rest of the piece is structured as follows: Section 2 provides a brief overview, Section 3 discusses the suggested model and approach, Section 4 presents the results and talks, and Section 5 summarizes the Conclusion.[22]

II. BACKGROUND

Artificial neural networks are an attempt at modeling the information processing capabilities of nervous systems. Many different kinds of non-linear issues that are challenging to tackle using conventional methods can be solved with the help of artificial neural networks. In essence, an artificial neural network is a collection of basic processing units, or neurons, that exchange analog signals with one another. Weighted connections between neurons carry these messages [24]. Every one of these neurons builds up its inputs and uses an internal activation function to produce an output. This output may be a component of the network output or an input for additional neurons. [7].

Three components make up a neural network: triggering, architecture, and learning method. function. Various learning methods exist to train neural networks. The learning mechanisms are categorized as- Supervised learning and Unsupervised learning [1].

One systematic way to train multilayer artificial neural networks is by propagating them backwards. It has a solid mathematical foundation. Three steps make up the back propagation training of the network: a) forwarding the input education pattern, b) calculating then the corresponding error, and c) adjusting the weights[27].

Back propagation is a gradient-descending technique that involves propagating the error backwards from the final layer to the hidden layer and then back to the input layer in order to compute the incline of the fault with respect to the value of the weights for a given input. The weights are modified using this manner based on the error function.[28] Therefore, the set of weights that lowest the error function is thought to represent the answer to the issue. Based on the discrepancy between the intended and actual outcome, the weights are reverse adjusted. There are some issues while training through this algorithm. These include slow training, trapping in local minima, and convergence to non-optimal solution. [29]

Numerous academics have attempted to use genetic algorithms to tackle these challenges on multiple occasions.[30] The natural evolution process, in which a population of a particular species adapts to the natural environment under attention, and genetic algorithms are comparable., a population of designs is created and then allowed to evolve in order to adapt to the design environment under consideration.[31] These algorithms have taken attention to solve optimizing problems. The most important advantage of the genetic algorithms is their ability to use accumulative information about the initial unknown search space in order to move the next searches in to useful spaces [32]. Unlike traditional non-linear optimization methods, GA looks for better solutions by keeping a population of the current solutions. Consequently, in order to solve the ATM planning problem, both these algorithms are blended together to gain benefits of optimal solution finding along with faster convergence.[35]

III. MATERIALS AND METHODS

The hybrid approach may be created by intersecting the principles of the genetic algorithm and back transmission mechanism as follows.:

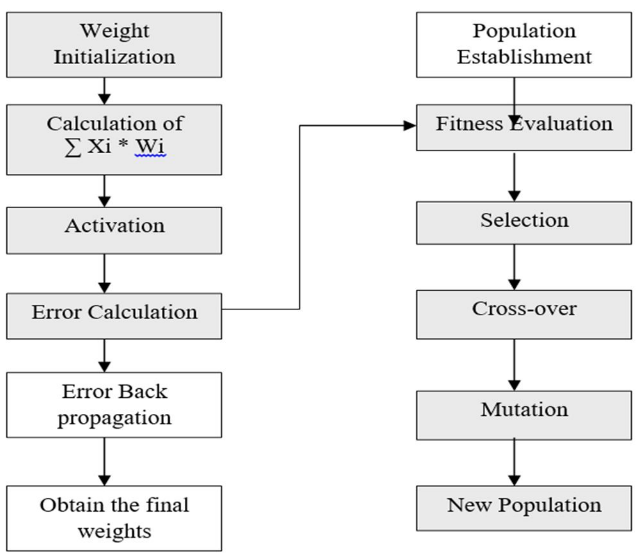

Figure 1 Point of intersection of genetic algorithms and replication genetic algorithms and replication

Because an individual's fitness increases with decreasing error value (diversion from planned output), (chromosome), the more are the chances of it to be selected for cross-over. The relation between error and fitness is given as follows:

$$error \propto \frac{1}{\text{fitness}}$$

As error is inversely proportional to fitness so clearly it is visible that at this stage, the hybrid approach is formed by the intersection of the genetic algorithm and the back propagation algorithm[37]. The main concept of the suggested method has been presented thus far. The primary task at hand is bringing this concept to life by developing and putting into use an artificial intelligence ATM forecasting framework based on heterogeneous neural networks [38].

The proposed hybrid neural network-based ATM prediction system begins with the gathering of ATM-related data, followed by normalization of the information, extraction of characteristics, training, and verification [39].

A. Collection of Data

The first stage in creating an ATM forecasting model is gathering ATM related data [40].

B. Normalization of Data

The normalization of data comes next after data gathering. Generally speaking, data with normalization yields greater results from neural networks. Utilizing the initial data in a network might lead to confluence issues [41]. In order to acquire the normalized data dnorm, all ATM data sets were converted into values between 0 and 1. This was done by dividing the variance between the actual value (dt) and the lowest possible value (dmin) by the discrepancy between the highest value (dmax) and the minimum value (dmin).:

$$d_{norm} = \frac{d_t - d_{min}}{d_{max} - d_{min}}$$

Normalization and weight initialization together serve the primary purpose of enabling the flattened activity act to function, at least in the early stages of the learning process. As a result, the gradient, which is determined by the nonlinearity's derivative, will never be equal to zero. To get the intended outcome, the outputs are finally de-normalized into the original data format [42].

C. Feature Extraction

In some circumstances, the attributes derived from historical data can be used to predict the ATM forecast. The features selected for this configuration aid in the forecast [43]. Correlating the features with the parameter to be estimated allows for the selection of the features since it offers the knowledge necessary to determine is a given feature is appropriate for the model and should be included in the data being provided set [44]. The following statistical markers can be utilized as model input features:

1) Day Numbers.
2) Weekday: Over a week, it is the day number; for example, Monday can be taken as 1, Tuesday as 2, and Sunday as 7.
3) Weekend Effect: It specifies the effect of weekend (Saturday and Sunday) on use of ATMs.
4) Salary Effect: It indicates the effect of salary drawn by people mostly in the starting of the month (on dated 1st to 3rd for each month etc.) on the use of ATMs.
5) Holiday Effect: It specifies the effect of holidays on the use of ATMs as people use ATMs mostly during holidays.

These chosen input characteristics after the analysis of data with respect to specific days like weekends, holidays and salary effect etc [45].

D. Training

In this phase the network is trained through collected data with various characteristics and how they affect the data is also considered [46].

E. Testing

The set of weights acquired during the exercise phase is used for testing. In this, the network receives inputs together with the final weights right away and we then receive the outputs.

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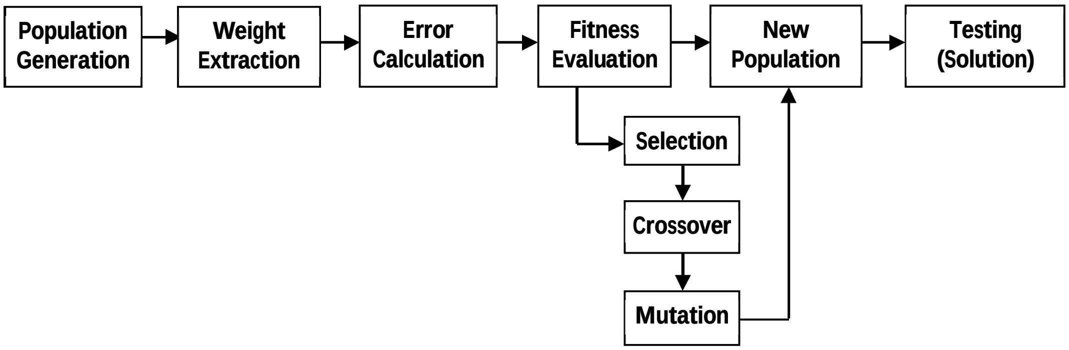

Figure 2: The block diagram of GA/BP based Hybrid Classifier

In genetic algorithm domain, a specific terminology based on natural genetics is followed (Goldberg, 2008)[47]. The word 'chromosome' is used to represent the alternative solution for the problem. In present problem, features extracted from fruit images act as 'genes' and set of such genes form the chromosomes. Set of chromosomes further form the 'population' of alternative solutions. The term 'weight' signifies the importance assigned to inputs, fed to the network. 'Error' means difference in the forecasted and desired outputs. 'Fitness' is how close an individual (alternative solution) to the desired solution. More the fitness of the individual, more suitable candidate it is for the solution. Fitness is always inversely proportional to the error value. 'Selection' operator indicates finding the two fittest individuals out of population of alternatives [48]. 'Crossover' operator implies merging of two parents (fittest alternatives) to reproduce a new offspring (new candidate solution). 'Mutation' operator means inculcating fresh features in the offspring to get diversity in the newly generated population.

The GA/BP NN algorithm works as follows:

- Step 1: Generate random the population of 'p' carriers (appropriate fixes for the issue).
- Step 2: Extract weights for input-hidden-output (l-m-n) layers from each chromosome x.
- Step 3: Determine the fitness f(x) of every genome x in the population by multiplying the values of the incremental errors acquired for every input set by two. (weather forecasting data).
- Step4: Repeat the actions that follow for developing an additional population until it is finished.
  - ➢ Selection: Choose two parent cells from a population based on fitness (the higher the fitness, the greater the likelihood of selection).
  - ➢ Crossover: To create additional offspring, cross over the parents (children). If there was no crossover that's the children are identical to their parent..
  - ➢ Mutation: Cross over the parents (children) to make more offspring. The offspring would be the same as their parents if there had been no crossover..
  - ➢ Acceptance: Place the fresh children within the new population.
- Step 5: Repeat steps 3 to 5 until stopping condition is met.

The output of classification step was in the form of text that specifies the class to which the fruit belonged to. Based on these classes, further grading was performed. The grading rules were: Assigning class A to non-defective fruit, class B to fruit having nominal surface defects and Class C to defective fruit. Hence, fruit grading was performed based on these rules [49].

IV. RESULTS AND DISCUSSION

A. Research Data

The ATM day-by-day credit information served as the research's source of data. The unnormalized form of the data just includes the amount removed. Following the raw data collection, this was carefully examined, and the impacts of several parameters—such as the weekend effect and holidays—were computed [50]. The set that is used for training and the set used for testing are the two chosen at random groups from which the set of patterns is split..

1) Training data: The artificial neural network has been trained using the data from the first thirty days..

2) Testing data: Data from the previous three days have been utilized for testing [50]..

B. Tools used

The tool used in this modelling setup is MATLAB 13.0.

C. Simulation

The suggested model makes use of a multifunctional feed forward architecture with one or more covert layers—that is, layers situated between the input and output layers—whose processing nodes are known as hidden neurons, or hidden units. The challenge heavily influences how the neural networks are configured. Therefore, depending on their knowledge, the designer must choose how many hidden layers and hidden layer nodes are acceptable. Thus, every program that uses the trial-and-error approach needs a suitable design. The target is used as the parameter to be predicted during the training process, and characteristics that were retrieved from the ATM data are applied as input samples

The 5-3-1 neural network design has been used to the BP/GA approach in this study. Five input neurons are used for expressing the day, week, weekend, salary, and trip effects. Three hidden layers are used for interpreting, and one output neuron is used to represent cash forecasts. The chromosomes have been coded using an actual coding scheme.

Up till the network receives training, this process is repeated. Testing is done using the set of weights acquired during the training phase after it has concluded. The initial values and final weights are sent into the network during the testing process, and we then receive the results back.

D. Calculation of Population Size

Setting the population is the first stage in the suggested approach. The length of a gene and the network architecture determine the number of people. A gene's length is presumed to be a fixed value. Here, it is presumed that a gene's length in this instance is five digits.. Below are given the network architecture and their corresponding population size in table 1 below:

Table 1 Calculation of Population Size

Network Architecture (l-m-n)	No. of weights w =(l+n)*m	Length of chromosomes cno = w*d	Population Size
5-1-1	(5+1)*1	6*5	30
5-2-1	(5+1)*2	12*5	60
5-3-1	(5+1)*3	18*5	90

E. Selection of Hidden Neurons

The choice of how many hidden neurons to include in the hidden layer is one of the main problems with neural network construction, as discussed in the section on current work. In order to compare MAPE values for various hidden neuron counts, population sizes, and the number of iterations needed to train the network to a minimal error value, these factors have been taken into account.

Here, a variable population size has been used to apply the hybrid approach. The program has been run and the error has been computed for each population value. The proportion of population fluctuations, the number of neurons in the layer of concealment, and the associated mean absolute percentage error values for the combined BP/GA approach are displayed in Table 2.

Table 2 Selection of Appropriate NN Architecture

Population Size	Hidden Neurons	Iterations	MAPE
30	1	190	1.10
60	2	340	0.86
90	3	400	0.42
120	4	482	1.47
150	5	525	1.85

The program has been run and the error has been computed for every individual value. The quantity of population fluctuations, the number of neurons in the hidden layer, and the related mean absolute percentage error values are displayed in Table 2. The data shown in Table 2 indicates that the population's size of 90 and the total quantity of hidden neurons, 3, correlate to the lowest MAPE value. Therefore, this population size will be used in the current setting for future study.

The suggested model makes use of a multilayer feed forward architecture with one or more hidden layers—that is, layers situated between the input and output layers—whose processing nodes are known as hidden neurons, or hidden units. The challenge heavily influences how the neural networks are configured. Therefore, depending on their knowledge, the designer must choose how many hidden layers and hidden layer nodes are acceptable. Therefore, 5-3-1 is the most suitable architecture that was selected for this application by trial and error. Figure 4.1 displays the error vs. iterations graph for NN design 5-3-1 and population count 90..

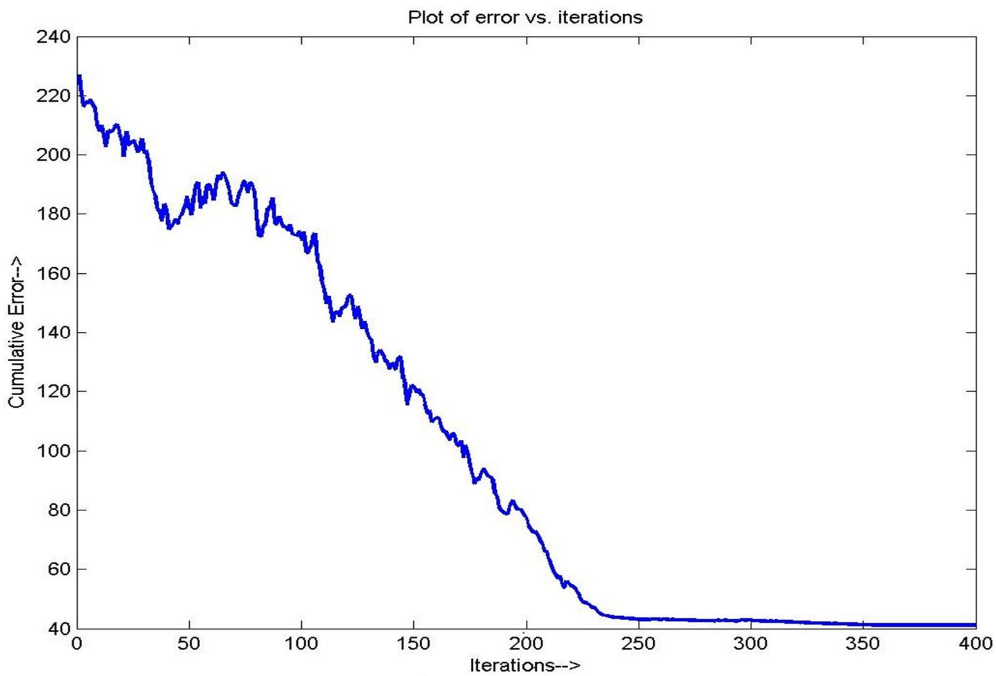

Fig 3 Error values aggregated for repeats with a population size of 90

F. Desired Output vs. Forecasted Output

The expected and intended outputs for the BP/GA approach are displayed in table 3, together with the error values correlating to day no. These error values are computed using.

Error Value = (Desired Output – Actual Output)

Table 3 Financial projections with backpropagation based on ascending gradients.

Day No.	Desired Output (in Lacks)	Forecasted Output (in Lacks)	Error Value
1	6.00	8.70	-2.70
2	2.50	8.52	-6.02
3	5.50	8.42	-2.92

The values in table 3 are represented graphically in figure 3 with number of days corresponding to cash target. In which red line shows the BP output and Black line shows the desired output.

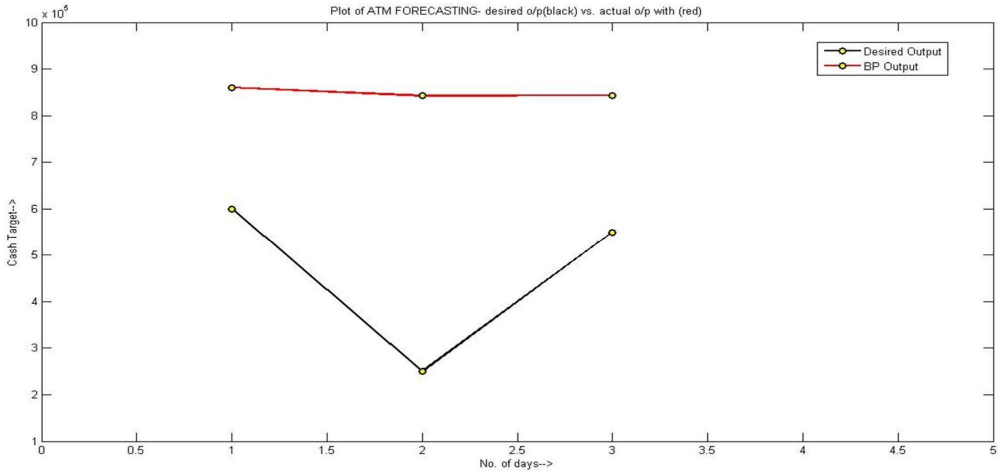

Fig. 4 ATM forecasting using BP based on gradient descent with the intended result

G. Comparison: BP-GD Technique vs. BP/GA Technique

Using data from the same day, the suggested combined BP/GA approach is compared against the conventional back propagation strategy based on gradient descent methods.

Table 4 Comparison of BP/GA and GD-BP Models for ATM Cash Forecasting

Day No.	Desired Output (in Lacks)	Output using GD-BP (in Lacks)	Error Value for GD-BP	Output using BP/GA(in Lacks)	Error Value for BP/GA
1	6.00	8.70	-2.70	3.70	2.30
2	2.50	8.52	-6.02	1.25	1.25
3	5.50	8.42	-2.92	4.80	0.70

The contrast shown above makes it abundantly evident that the integrated BP/GA approach, as opposed to the conventional gradient-based forward propagation method, is more appropriate for ATM forecasting. Compared to the back propagation method, the suggested integrated back propagation based genetic algorithm technique is closer to the intended result. Figure 5 shows a visual representation of the aforementioned values. Figure 6 shows the bar chart comparing the BP-GD and BP/GA approaches for ATM forecasting.

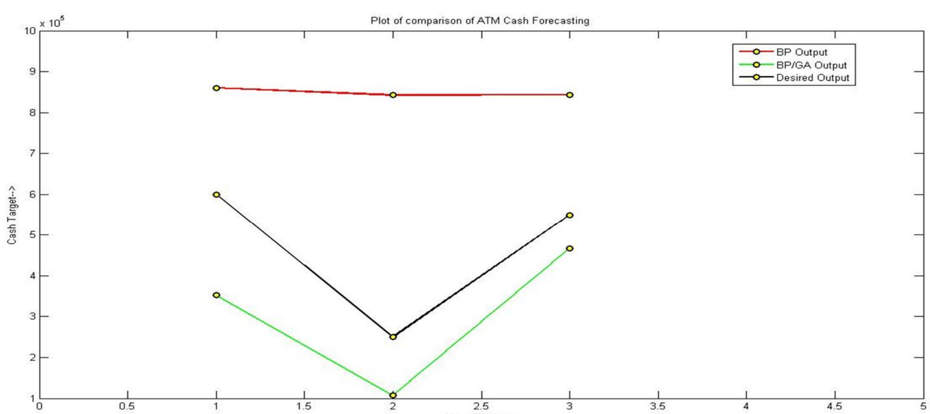

Fig. 5 Comparison of BP/GA and gradient/BP models for ATM forecasting

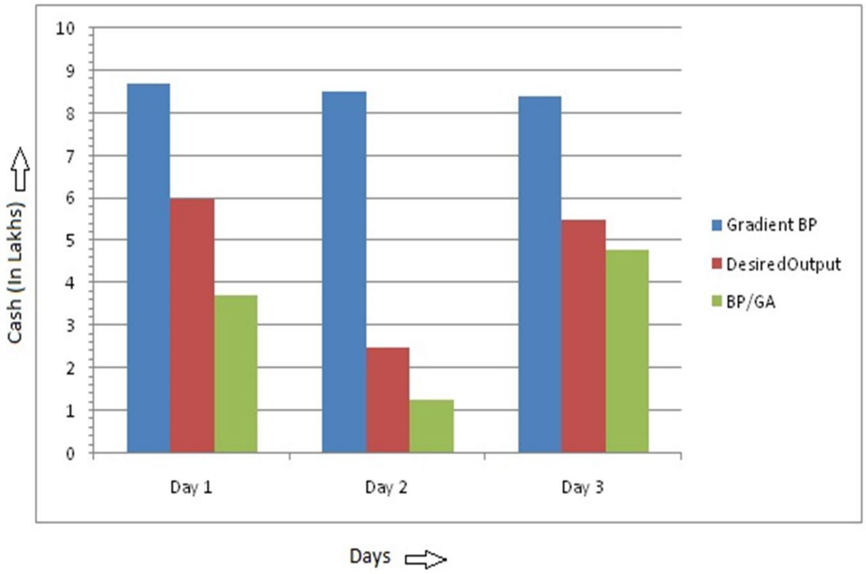

Fig. 6 Comparison of BP/GA and gradient/BP for ATM forecasting

The aforementioned comparison unequivocally demonstrates that the combination of BP/GA approach is better suited to forecast ATM than the conventional gradient-based back propagation algorithm since the former is closer to the intended output when it comes to ATM forecasting..

V. CONCLUSION

An automated teller machine (ATM) is a computerized communication device that allows consumers of insurance companies to conduct payments in a public place without the assistance of a human clerk. More banks are focusing on improving the efficiency of how they handle cash at ATMs as of late. Capturing and analyzing previous data to yield future insights is essential to the ATM's forecasting algorithms. Recently, several writers have tried to estimate and forecast the demand in order to optimize the cash. Nonetheless, the dependability of these methods may be impacted by the underlying stochastic cash demand process's high volatility and non-stationarity. In addition, the demand for cash is not only impacted by time but also exhibits various trends that exacerbate the difficulty of modeling. For instance, weekends, holidays, the end of the month, festival days, etc.

The aforementioned study makes it simple to see how back propagation algorithm (BP) and genetic algorithm (GA) are compensable. The hybrid approach combines the benefits of both BP and GA to learn effectively. If one considers solely the need for global searching, the suggested method is more suited for neural networks. It performs well on global searches (as opposed to one-way searches) and operates on a population of points rather than a single point. Additionally, it combines the benefits of stochastic optimizing algorithm GA with deterministic gradient-based algorithm BP. GA is not as speed-efficient as the hybrid approach, which makes effective use of local gradient information. Hence, the ATM forecasting system is suggested to adopt a hybrid genetic based back propagation approach.

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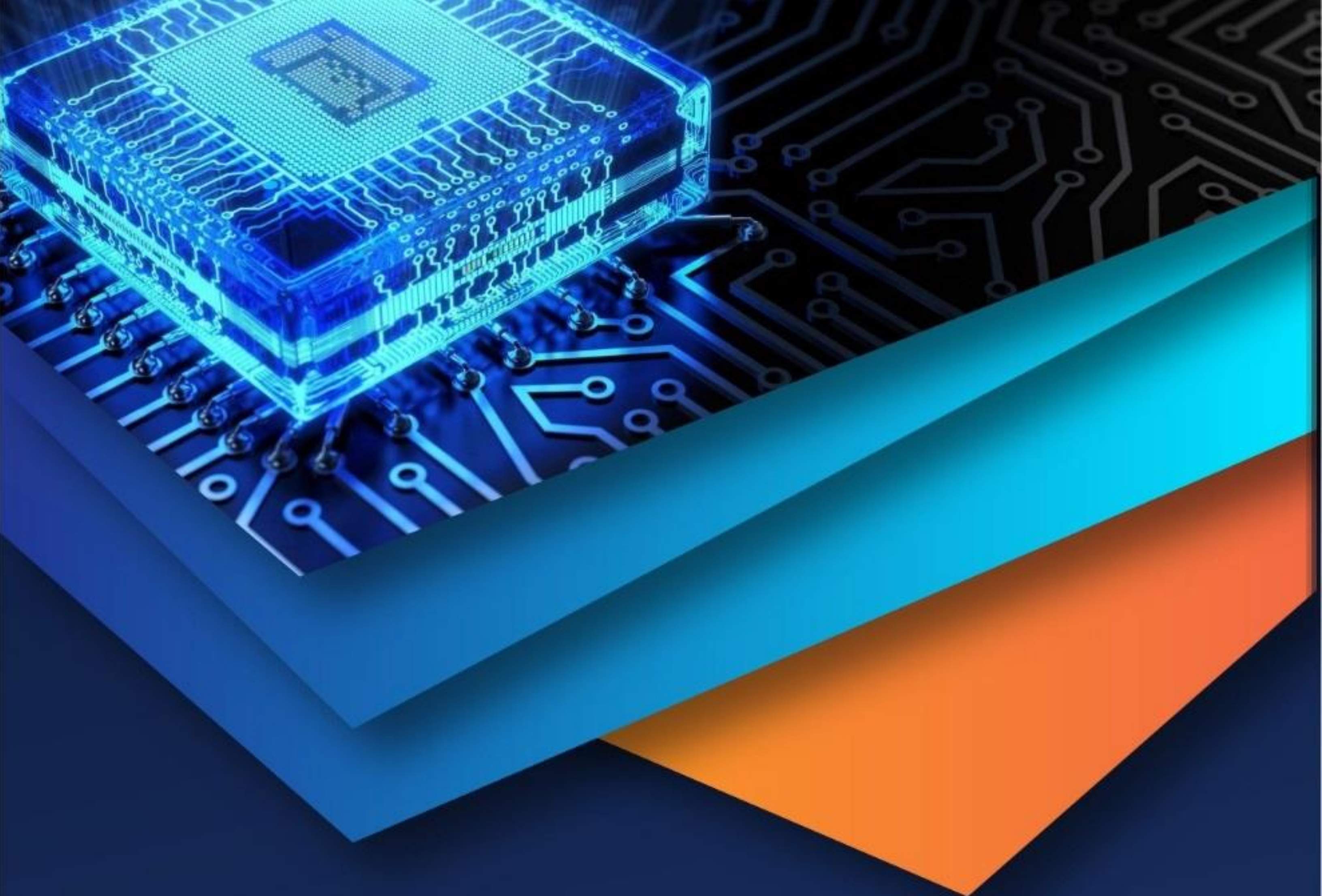

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