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DESIGN OF FINANCIAL DATA ANALYSIS AND DECISION SUPPORT SYSTEM BASED ON BIG DATA

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Abstract. A cutting-edge Decision Support System (DSS) utilizing Deep Reinforcement Learning (DRL) for improved financial data analysis is the primary focus of the proposed research. In light of the prospering difficulties presented by large information in the monetary space, our creative methodology outfits the force of DRL to foster a powerful and versatile framework. By flawlessly incorporating DRL into the DSS structure, we mean to improve the framework's capacity to break down huge and complex monetary datasets. This DSS not only provides financial professionals with intelligent decision-making support but also real-time insights into market trends and patterns. The collaboration between enormous information investigation and DRL works with a dynamic and responsive framework equipped for adjusting to the quickly developing financial scene. Our exploration adds to the headway of choice by tending to the particular requests of monetary information, consequently enabling clients with ideal and informed dynamic abilities. The proposed DRL-based DSS addresses a change in perspective in monetary information examination, offering a versatile and effective answer for exploring the intricacies of enormous information in the financial area. This examination holds huge potential for changing dynamic cycles, advancing monetary security, and at last adding to the progression of the more extensive monetary industry.

Key words: DRL, decision support system, financial data analysis, big data, intelligent decision making, adaptive technology

1. Introduction.

In the current financial landscape, intelligent decision support systems are in high demand. These frameworks act as priceless instruments for monetary experts, offering experiences, examination, and dynamic help [4]. Regardless, standard financial decisions and genuinely strong organizations experience basic limitations in really managing the intricacies of present day money related data. Continuous handling of immense datasets, adjusting to quickly moving economic situations, and removing helpful data from multi-faceted monetary examples are snags [6, 7]. Because of these limitations, standard frameworks are unable to be deft and responsive, which results in subpar dynamic results and hampers the ability of financial experts to investigate the powerful concept of the financial world [12].

As we analyse the continuous creative part, existing solutions for money related decisions assist with showing drawbacks that warrant thought. Conventional progressions fight to keep awake with the surprising improvement of colossal data in the financial region, habitually provoking lethargy issues and compromised logical accuracy [8, 9]. The weaknesses to these advancements feature the pressing precondition for novel systems that can beat the challenges presented by the consistently expanding volume and intricacy of monetary information. Significant learning emerges as a promising street to address the lack of ordinary money-related decisions and sincerely strong organisations [10]. Its ability to subsequently acquire depictions from data benefits from more exact and nuanced examination. Monetary choice emotionally supportive networks can possibly turn out to be stronger and versatile thanks to profound learning procedures' capacity to remove includes and perceive designs. This impact in context opens approaches to the extra present day and strong procedures for unravelling complex money related data, empowering prevalent powerful cycles.

By clearly analysing the limitations and restrictions of the existing techniques here we proposed the novel approach of Deep Reinforcement Learning based Decision Support System (DRL-DSS) [1, 11, 5]. This combination means bridling the qualities of both profound learning and support, figuring out how to make a framework that not only explores the difficulties of large amounts of monetary information but also adjusts progressively to changing economic situations. By coordinating DRL into the choice help structure, our exploration looks to provide a versatile, responsive, and smart arrangement, engaging monetary experts with upgraded dynamic capacities notwithstanding the developing monetary scene.

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The motivation behind our research on the "Design of a Financial Data Analysis and Decision Support System Based on Big Data" stems from the increasingly complex and voluminous nature of financial data in the global economy. The explosion of big data in the financial sector presents both a significant challenge and a golden opportunity for financial institutions. Traditional economic analysis tools and methodologies are becoming inadequate to process, analyse, and derive meaningful insights from this vast amount of data efficiently. As a result, there is a pressing need for innovative solutions that can handle the complexity and scale of financial data while providing actionable insights to support decision-making processes.

Integrating Deep Reinforcement Learning (DRL) with a Decision Support System (DSS) represents a pioneering approach to tackling the challenges posed by big data in finance. DRL, with its ability to learn optimal actions through trial and error by interacting with a dynamic environment, offers a powerful tool for analysing financial datasets that are large, complex, and constantly changing. By leveraging DRL, our proposed DSS aims to not only process and analyze big financial datasets more efficiently but also adapt to new data and market conditions in real-time, providing financial professionals with timely and relevant insights.

The main contribution of the paper as follows

1. Proposed a novel approach of Deep Reinforcement Learning Decision Support System (DRL-DSS) that significantly enhances the decision support capabilities in the financial domain.
2. This research contributes to addressing the challenges posed by big data in financial systems.
3. The proposed DRL-DSS includes a DRL-DQN-based technique in the decision support framework; this intelligent technique enables the system to learn and adapt to market conditions autonomously and offers a better path in financial decision-making that goes beyond the capabilities of traditional systems.
4. This proposed efficacy is proved with valid experiments.

2. Related Work.

2.1. Decision support system based discussions. This study [14] investigates how big data in financial decision-making affects information asymmetry, principal-agent relationships, and risk management. It examines how big data could enhance predictions, increase the relevance of decisions, provide companies a competitive edge, and promote flexible decision-making. The research emphasises the value of big data in merging business and finance and the necessity of a robust information infrastructure for this type of integration through examination of practical instances of its application in corporate financial decisions. According to the study, big data is crucial for removing obstacles between business and finance, expediting the decision-making process, and raising company value. This study [5] highlights flaws, including inefficiency and intelligence deficiency, in the present financial decision support systems, and investigates how artificial intelligence might be integrated to improve them. Using the X business as a real-world example, it suggests cutting-edge, clever computerised technology to help with financial decision-making. Based on a questionnaire survey, the results demonstrate that the AI-enhanced system offers higher intelligence, timeliness, and accuracy in financial decision-making while lowering costs and simplifying the integration of management and financial accounting.

The goal [3] of this study is to help businesses make better financial decisions by utilizing the current data boom. It emphasizes how crucial timely data analysis and intelligent systems are to the efficient management of resources, time, and choices in order to maximize profitability. The article highlights the applicability of edge computing and criticizes conventional data management in businesses as being out of date. It then suggests an information-based financial management system. The system meets performance metrics requirements with high efficiency, responsiveness, and CPU usage after extensive testing and modifications. The whale algorithm's integration also demonstrates excellent energy and computational resource management. The system's potential to enhance enterprise financial management is highlighted in the study's conclusion, which also calls for more improvement.

This study [16] shows how big data may improve financial analysis and decision-making in businesses, replacing more conventional approaches that depend on human resources. The study highlights notable enhancements in decision-making accuracy and efficiency through the use of an intelligent financial decision support system that incorporates big data web crawler technology and ETL procedures, as demonstrated in a case study involving J Group. The system's ability to analyse data in real time and provide financial insights represents a significant advancement in corporate financial management and decision-making. This work [15] fills a need in basic medical care, particularly in distant areas, by creating a ground-breaking artificial intelligence system that can speak with patients on its own using voice recognition and synthesis. The system works as a virtual doctor. The AI system's promise to provide precise probability forecasts for patient diagnosis is demonstrated by its ability to foresee type 2 diabetes mellitus utilizing non-invasive sensors and deep neural networks. The study also examines the level of acceptance of artificial intelligence among young people in the healthcare industry, including details on the possible long-term effects of this kind of technology. Artificial intelligence has been used more and more in the legal industry since the 1980s to handle an increase in the number of cases. This paper introduces "TaSbeeb," a deep learning-based JDSS that can retrieve religious texts and judicial reasoning for use in Saudi courts. It is divided into three stages: using stacked DL models to handle unbalanced classification, semi-automated judicial text annotation, and a judicial language model for information retrieval. With its excellent accuracy and F-scores, TaSbeeb represents a substantial improvement in the efficiency and accuracy of Arabic JDSS and holds the potential for wider implementation in judicial systems.

3. Methodology.

3.1. Proposed Overview. The suggested idea for the DRL-DSS coordinates both DRL-DQN and TRPO calculations to break down and settle on choices in the complex and information-serious field of money is shown in Figure 3.1. At first, the framework gathers an exhaustive cluster of monetary information, including stocks, securities, market lists, macroeconomic pointers, and ongoing worldwide monetary news. This information is carefully preprocessed to guarantee quality and importance, utilizing procedures like standardization, sound decrease, and element choice. The DRL-DQN algorithm is used in the first phase. This includes the utilization of a profound Q-organization that is prepared to comprehend and expect market patterns and ways of behaving. The DQN is intended to deal with the tremendous time-series information, perceiving examples and gaining from verifiable patterns to make informed expectations about future market developments. This organization is advanced for security and effectiveness, utilizing procedures, for example, experience replay and fixed Q-focuses, to improve learning. Parallelly, the TRPO calculation is used to advance the dynamic approach of the framework. TRPO, known for its viability in overseeing strategy slope techniques in support learning, offers a more steady and hearty way to deal with learning strategies. It guarantees that the updates to the strategy are made inside a trust locale, forestalling uncommon arrangement changes that could prompt shaky preparation or lacklustre showing. This is especially vital in the unstable and variable monetary business sectors.

The framework orchestrates the forecasts and experiences acquired from the DRL-DQN with the approach choices made through TRPO. DQN provides deep insight into the data, and TRPO ensures that the decision-making process is continuously refined and optimized for the best possible outcomes. To address the difficulties of enormous information in finance, high level information, the board, and dimensionality decrease procedures are carried out. These procedures help in refining the most effective data from the tremendous datasets, guaranteeing that the DRL-DQN and TRPO calculations are working with the most applicable and huge information highlights. Far-reaching back-testing and forward-testing instruments structure a vital piece of the procedure. The situation is thoroughly tried against verifiable information and simulated conditions to approve its viability and flexibility in various economic situations. The DRL-DSS's robustness and dependability in real-world financial scenarios are assured by this extensive testing. At long last, an accentuation is put on making an interpretable and easy-to-understand interface for the DRL-DSS. Users are able to make well-informed decisions based on the system's insights and recommendations as a result of this, guaranteeing that the intricate workings of the DRL-DQN and TRPO algorithms are presented in an approachable manner. This approach expects to make the DRL-DSS a strong and natural device for monetary examination and dynamics in the space of enormous information.

3.2. Proposed DRL-DSS Approach in Financial big data.

3.2.1. DRL-DQN based Financial Decision Making. DQN is a useful tool for making well-informed judgments in the financial domain when used in conjunction with a DRL-DSS. To control the current status of the market it analyses a lot of financial data, including stock prices and market movements. Then, by assessing the anticipated advantages of different financial transactions, like purchasing or selling stocks, it makes predictions about their likelihood to be successful. The DQN regularly analyzes market behaviour to refine its approach to making decisions by identifying what works and what doesn't. Because of this, it is a

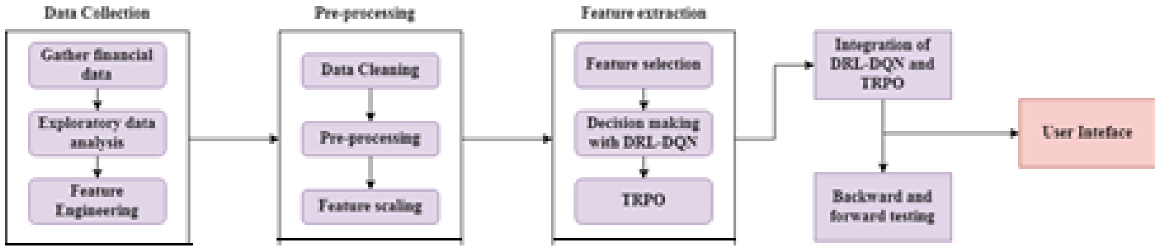

Fig. 3.1: Proposed DRL-DSS Architecture

priceless tool for financial trading investment advice and automated decision-making, assisting in maximizing returns and lowering risks**.** Some of the DRL-based decision support systems are discussed in the study [2, 13].

The system is designed to collect only the data necessary for the specific purposes for which it is processed, adhering to the GDPR principles of data minimization and purpose limitation. It incorporates robust consent management mechanisms to ensure that data is collected and processed only after obtaining explicit consent from individuals, in line with GDPR requirements. To protect personal data, the system employs data anonymization techniques and encryption to ensure that individual identities cannot be traced. This approach safeguards personal information against unauthorized access and data breaches.

Algorithm 1 DRL-DQN based Financial Decision Making

Input: $n_{min}\,(minimum\ experience\ replay\ size)\,, n_{max}\,(maximum\ experience)\,, \Delta\,(learning\ rate)\,, \alpha\ \ (exploration\ rate)\,, \gamma\,(discount\ factor)\,,\ \delta\,(random\ action\ probability)$
Output: Financial decision making strategy
Initialize replay memory $rpme$ to capacity n (to store diverse market scenarios)
Initialize action value function Q with random weights θ
Initialize target action value function $\widehat{Q}$ with weights $\theta = \ \theta^{-}$
For episode $= 1, M$ do –number of episodes representing different market conditions
Initialize sequence $S_1 = \{X_1\}$ and preprocessed sequence $\sigma_1 = \sigma_1(S_1)$
For $t = 1, T$ do (decision points of financial data)
with probability δ select a random action A_t (explore the action space)
otherwise select $A_t = \max_A Q(S_t, A, \theta)$ (exploit the learned strategy)
Execute action A_t and observer reward R_t and next state X_{t+1} –based on financial outcome
Set $S_{t+1} = S_t, A_t, X_{t+1}$ and preprocess $\sigma_{t+1} = \sigma(S_{t+1})$
Store transition $(\sigma_t, A_t, R_t, \sigma_{t+1})$ in replay memory $rpme$
Sample random minibatch of transitions $(\sigma_J, A_J, R_J, \sigma_{J+1})$ from replay memory $rpme$
Set $Y_j = \left\{ R_{J+\gamma} \max_A \genfrac{}{}{0pt}{}{R_J}{\hat{Q}(S_{J+1}, A', \theta^-)} \right\}$ for non terminal states or $Y_J = R_J$ for terminal states
Perform gradient descent step on $(Y_J - Q(S_J, A_J, \theta))^2$ with respect to the network
Parameters ϑ
Every C steps reset $\hat{Q} = Q$
End inner loop
End outer loop
Online financial decision making phase
Load the parameters ϑ;
Calculate action-value Q for the current financial state $(S_t, A; \theta)$
Output $A_t = argmaxQ(S_t, A; \theta)$ based on the learned policy

The algorithm explains how the DQN in a DRL framework is used to make financial judgments. The first step is to set up a replay memory system, which is a memory system that stores a variety of market scenarios. Two different kinds of action value functions are first allocated random weights when this memory is first used. After that, the algorithm runs through a number of episodes, each of which represents a distinct set of market circumstances. Every episode begins with the financial data series being set up, and at each time step, decisions are made iteratively. To balance the discovery of novel methods with the exploitation of proven lucrative ones, a combination of randomly picked actions and those chosen based on the greatest anticipated value from the Q-function are used in the decision-making process. The algorithm learns from the actual results of its judgments by watching the reward that results from its actions and the subsequent status of the market. The replay memory contains these events. It updates its knowledge by sampling a batch of these events on a regular basis. It does this by adjusting the network parameters through a process known as gradient descent, which improves future predictions. In order to prevent the algorithm from deviating too far from its most recent known effective method, this update occurs in cycles. The algorithm proceeds to an online decision-making stage upon the completion of the iterative learning cycles. Here, based on its forecasts and acquired information, it utilizes the factors it has learnt to assess the present financial situation and choose the optimal course of action, such as purchasing or selling assets. Because of this procedure, the algorithm becomes a dynamic instrument for financial decision-making that is always learning from and adjusting to the shifting conditions of the financial market.

LearnFlex utilises a cloud-based infrastructure for dynamic scaling based on real-time demand. This ensures that server capacity can be quickly adjusted to handle spikes in user access, particularly during peak times like the start of new courses or examination periods. The system employs advanced load-balancing techniques to distribute traffic evenly across servers, preventing any single server from becoming a bottleneck. This enhances performance and ensures a smooth and responsive experience for all users.

The DSS ensures transparency in trading activities and decision-making processes by maintaining detailed logs and reports. This aligns with MiFID II's requirements for transparency and accurate reporting to regulators. By employing advanced analytics, the system helps identify and mitigate market abuse and ensure fair trading practices, thereby supporting the integrity of financial markets as envisaged by MiFID II. The system is designed to analyse a wide range of data to ensure that trades are executed at the best possible terms for clients following MiFID II's best execution requirements.

3.2.2. TRPO (Trust Region Policy Optimization). TRPO is a critical component of the proposed DRL-DSS that helps the system make dependable and efficient financial judgments. TRPO is an advanced algorithm that works to gradually enhance the system's decision-making policy without bringing about abrupt or unstable modifications. Its primary goal is to gradually adjust the system's approach so that it may pick up new information and experiences without deviating too much from its prior understanding. This is especially crucial in the irregular and turbulent world of finance, where it's necessary to strike a balance between trying out novel tactics and upholding a certain standard of dependability and consistency. Through the use of TRPO, the DRL-DSS is able to minimize the danger of large policy swings that might result in subpar performance or unanticipated losses while also learning gradually and making increasingly educated judgments. This allows the system to adapt to the constantly shifting financial markets.

Algorithm 2 Trust Region Policy Optimization

Initialize π_0 suitable for financial market scenarios
for do$i = 0, 1, 2 \ldots\ldots$ Until convergence do
  Compute all advantage values $a_{\pi_i}(S, A)$
  Solve the constrained optimization problem to update the policy
  Update the policy using $\pi_{i+1} = arg\min_\pi [L_{\pi_i}(\pi) + \left(\frac{2\in\gamma}{(1-\gamma)^2}\right) D_{KL}^{max}(\pi_i, \pi)]$
  where $\in = \max_S \max_A |A_\pi(S, A)|$
  And $L_{\pi_I}(\pi) = \mu(\pi_i) + \sum_S P_{\pi_i}(S) \sum_A \pi(A|S) A_{\pi_I}(S|A)$
  Repeat the steps 2-4 until the policy converges
end for

Enhancing decision-making methods in a stable and regulated manner is the goal of the improved TRPO for a DRL-DSS in financial situations. First, a policy, represented by π_0, is initialized. This establishes the starting point for financial choices such as purchasing, disposing of, or retaining assets. After that, the algorithm refines this strategy iteratively. The advantage values for the current policy are initially determined by the

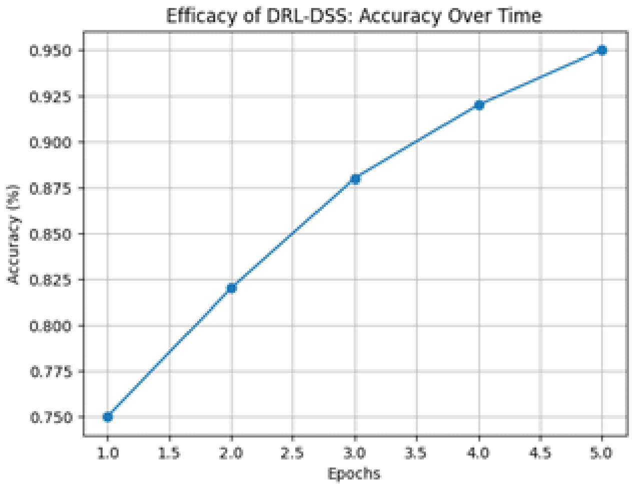

Fig. 4.1: Accuracy

algorithm in each iteration. When deciding whether to purchase or sell stocks, for example, these numbers indicate how much better or worse a certain action is in comparison to the typical action in that particular financial situation. This is a critical stage in determining how successful the market's present decisions are. The method then resolves an optimization issue using constraints. The goal of this stage is to identify a new policy that marginally outperforms the existing one. Here, stability must be maintained by ensuring that the new policy doesn't stray too far from the previous one. This is especially crucial in the banking industry because of how irregular and unsettled the markets can be. A precise formula that strikes a compromise between making improvements and adhering closely to the prior version of the policy is used to update it. It restricts the amount of change to prevent significant deviations and takes into account how much the projected return on financial activities would increase under the new policy. Eventually, this procedure is carried out again until the policy converges, or reaches a point at which it no longer changes significantly. This suggests that the system has discovered a reliable and efficient method for deciding how to allocate funds. The financial industry, where reliability and performance are crucial, is a perfect fit for the TRPO because of its emphasis on steady development.

4. Results and Experiments. We move further with the evaluation of the suggested innovative DRL-DSS based on the study [16].

4.1. Evaluation Criteria. The performance of the suggested DRL-DSS across several epochs demonstrates its remarkable efficacy in Figure 4.1. The accuracy increases clearly and consistently throughout the course of five epochs, rising from 0.75 in the first epoch to 0.95 by the fifth. This pattern suggests that the system is picking up new skills and becoming more adept at what it does. It is especially remarkable that the last epoch reached a high degree of precision, at 0.95. It indicates that 95% of the time the DRL-DSS makes accurate judgments or predictions, which is a powerful testament to its efficacy and capabilities. Furthermore, the notable increase in accuracy in just five epochs demonstrates the system's capacity for quick learning. This is an essential characteristic in the dynamic and fast-paced field of financial data analysis, where the capacity to swiftly adjust to new knowledge and market developments is priceless. In addition, the system's dependability is demonstrated by the continuously high accuracy rates throughout all epochs. A consistent performance like this indicates that users may rely on the DRL-DSS to provide reliable and accurate forecasts or choices, which confirms the tool's appropriateness for financial analysis and decision-making.

The accuracy and recall values of the proposed DRL-DSS may be evaluated throughout a sequence of epochs, which correspond to discrete time intervals in the systems learning and operating phases, as shown in Figure 4.2. The accuracy values show a progressive rise over the period of five epochs, peaking at 0.92 and

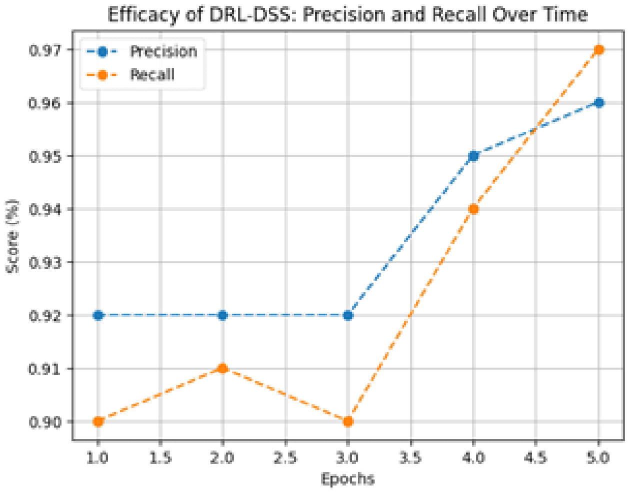

Fig. 4.2: Precision and recall

eventually reaching 0.96 by the fifth epoch. The system's capacity to correctly identify relevant cases without overextending to irrelevant ones is demonstrated by its consistency and increasing trend in precision. This is an important feature in financial decision-making, where accuracy in forecasts or classifications is critical. In a similar vein, the recall values show how well the system recognizes all relevant occurrences; they begin at 0.90 and increase to 0.97 by the fifth epoch. The increase in recall indicates that the system is getting better at catching all possible opportunities or threats as it develops, which is a crucial attribute in dynamic financial contexts where it can be expensive to overlook important information. High recall and accuracy numbers combined over all epochs show the efficacy of the DRL-DSS. As demonstrated by the precision and recall figures, the system not only keeps up a high degree of prediction accuracy but also makes sure that all important data points are identified. This balance is especially important in financial contexts, where decision-making results can be greatly impacted by the accuracy of forecasts as well as the completeness of information gathered.

An excellent way to assess the effectiveness of the suggested DRL-DSS is to examine its F1-Score values across a number of epochs present in Figure 4.3. An impartial assessment of the accuracy and completeness of the system in forming judgments or predictions is given by the F1-Score, which is a harmonic mean of precision and recall. The F1-Score values, in this case, throughout the course of epochs are 0.89, 0.90, 0.92, 0.92, and 0.96, respectively. We can clearly observe an improving trend in these ratings as they develop. The DRL-DSS exhibits a steady increase in its decision-making efficacy, beginning with a comparatively high score of 0.89 in the first epoch and ending with a score of 0.96 by the fifth. This increasing trend shows the system's strong initial performance as well as its capacity to successfully learn and adapt over time. In particular, the system's final F1-Score of 0.96 indicates a high degree of accuracy and dependability in its predictions, suggesting that it covers a wide variety of pertinent cases and makes the right selections the majority of the time. Such performance is suggestive of a system that can reduce false positives and negatives in addition to being proficient at accurately detecting and acting upon relevant data items. This is particularly important since errors can have a big cost in the dynamic and intricate field of financial data analysis.

5. Conclusion. In conclusion, the DRL-DSS that has been suggested has shown to be incredibly effective when it comes to financial data processing. The system's strong capacity to make comprehensive and precise financial decisions is demonstrated by the steady increase in key performance indicators over time, especially the F1-Score. The F1-Score values of the DRL-DSS have been growing consistently from 0.89 to 0.96, demonstrating the model's ability to cover a wide range of relevant financial scenarios in addition to producing accurate forecasts. The F1-Score captures this balance between recall and accuracy, which is critical in the volatile and

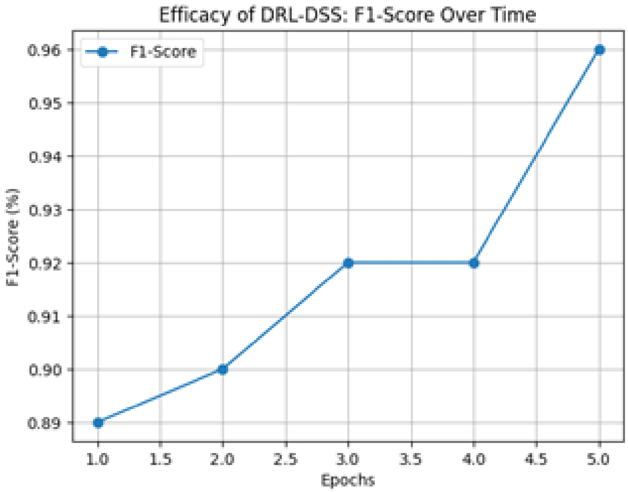

Fig. 4.3: Efficacy of DRL-DSS: F1-Score over time

complicated field of finance where decisions can have far-reaching effects. The system is a very dependable and useful tool for financial experts because of its capacity to adapt and learn over time, as shown by the rising trend in its performance indicators. It offers evidence of the potential benefits of incorporating cutting-edge machine learning methods into decision support systems, such as deep reinforcement learning. The development of intelligent financial decision-making tools has advanced significantly with the DRL-DSS's ability to navigate the complexities of financial data analysis. This study establishes a standard for the creation of complex, data-driven decision support systems in the banking industry and beyond, and it opens the door for future developments. Future developments will likely focus on refining and advancing DRL models to enhance their predictive accuracy, efficiency, and scalability. This includes exploring cutting-edge neural network architectures, reinforcement learning strategies, and algorithmic improvements to better handle the nuances of financial data and decision-making processes.

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