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Research Article

Intelligent Designed Assistance Model to Evaluate the Role of Social Media Marketing in Promoting Investment in Mutual Funds in India

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Abstract: This research article explores the impact of social media marketing on promoting investment in mutual funds in India. With the increasing penetration of the internet and the rise of social media platforms, financial institutions are leveraging these channels to engage potential investors. The study investigates the effectiveness of social media marketing strategies in influencing investor behavior, awareness, and decision-making regarding mutual funds. A mixed-method approach was employed, including surveys and interviews with industry experts and investors. This paper explores the application of the Intelligent Designer Assistance System (IDAS) in mutual fund analysis, offering a comprehensive framework for evaluating mutual funds based on key financial metrics. IDAS integrates multiple parameters such as risk levels, return on investment (ROI), cost efficiency, volatility, Sharpe ratio, beta, fund size, and manager tenure, among others, to provide insights that assist investors in making informed decisions. Through the analysis of various fund types, including equity, bond, balanced, and sector funds, this study demonstrates how IDAS can tailor investment recommendations according to individual risk preferences and financial goals. The findings emphasize the importance of aligning investment strategies with factors like fund performance consistency, adaptability to market conditions, and overall cost-effectiveness. This approach enables investors to optimize their portfolios by selecting funds that best match their risk tolerance, return expectations, and sector interests, leading to more strategic and efficient investment choices. This paper investigates the role of social media marketing in promoting investments in New Fund Offers (NFOs) within the Indian mutual fund landscape. As financial institutions increasingly leverage social media platforms for marketing, understanding their effectiveness in influencing investor behavior becomes crucial. This study employs a mixed-method approach, including quantitative surveys and qualitative interviews, to analyze how social media impacts awareness, engagement, and investment decisions related to NFOs.

Keywords: Social Media Marketing, Intelligent Marketing, Mutual Funds, Investment Behavior, Financial Services.

1.Introduction

The Indian mutual fund industry has witnessed substantial growth in recent years, driven by increased awareness and accessibility [1]. Social media marketing has emerged as a vital tool for financial institutions to reach potential investors and promote mutual fund investments. This study aims to analyze how social media marketing strategies impact investor awareness, engagement, and decision-making in the context of mutual funds [2]. In recent years, social media marketing has emerged as a powerful tool for financial institutions, especially in promoting awareness of mutual funds. The mutual fund industry in India has experienced rapid growth, particularly with the introduction of New Fund Offers (NFOs) [3]. NFOs present an opportunity for investors to participate in newly launched mutual funds, often accompanied by marketing campaigns aimed at generating interest. Social media marketing has become a pivotal strategy for financial institutions to engage potential investors and promote these offerings [4]. The accuracy, and cost-effectiveness of design outcomes while being capable of dynamically adjusting to the evolving needs of users.

The first step in the proposed system is the collection of data from the UrbanScene3D dataset, which offers a rich source of spatial information required for architectural design. This dataset contains detailed [5]. 3D models of urban environments that provide valuable insights into architectural space planning. However, raw data often contains noise that can interfere with the design process [6]. To clean and enhance the data, Low-Pass Virtual Filtering (LPVF) is applied. This pre-processing step effectively removes irrelevant data, improving the quality of the input data and ensuring that only the most relevant features are used in the design process. Once the data has been pre-processed, it is fed into an SNN, a biologically inspired model that mimics the behavior of neurons in the human brain [7-9]. SNNs are particularly suited for tasks that require the processing of event-driven and time-sensitive data, making them ideal for handling the dynamic nature of architectural design [10]. Unlike traditional neural networks, SNNs can model complex spatial and temporal relationships within a design, enabling real-time adjustments based on continuous feedback from users. This capability is essential for architectural design, where changes can occur frequently and where design solutions must be flexible and adaptable [11].

To further enhance the performance of the SNN, Hawk-Eye Optimization (HEO) is integrated into the system. HEO, inspired by the hunting strategies of hawks, is an optimization technique that is highly efficient in exploring large, complex solution spaces [12]. It dynamically adjusts the parameters of the SNN, helping the system converge on optimal design solutions. This integration of HEO and SNN allows the system to perform a more effective search of the design space, ensuring that the generated architectural designs are both efficient and cost-effective [13]. The optimization process in HEO helps the system balance competing objectives, such as space utilization, user preferences, and cost constraints, while ensuring that the designs are feasible and aligned with the client's requirements. While Artificial Intelligence (AI) has significantly impacted various fields, including architecture, current AI-driven design systems face several challenges that hinder their full potential [14]. One major issue is the overreliance on predefined design parameters, which results in designs that are overly standardized and lack the flexibility to accommodate evolving user needs or changes in environmental factors. Traditional optimization techniques, such as genetic algorithms or deep learning models, struggle to capture the dynamic, spatial, and temporal complexities of architectural design. Additionally, these systems often fail to adapt to real-time user feedback or changing constraints during the design process [15]. There is also a lack of integration between biologically inspired neural networks, like Spiking Neural Networks (SNNs), and advanced optimization methods like Hawk-Eye Optimization (HEO). The absence of such integration limits the ability of current design tools to generate innovative, personalized solutions while optimizing multiple objectives (e.g., cost, energy efficiency, space utilization). Thus, there is a critical need for a more adaptive, efficient, and responsive AI system for architectural design that can handle complex, time-varying constraints and user-driven adjustments in real time [16].

The primary contribution of this research is the development of an Intelligent Designer Assistance System (IDAS) that integrates Spiking Neural Networks (SNNs) with Hawk-Eye Optimization (HEO) to address the aforementioned gaps in existing systems. By combining the adaptive learning capabilities of SNNs with the exploration efficiency of HEO, the proposed system is able to dynamically adjust to user inputs, optimize the design space in real-time, and generate highly personalized and cost-effective architectural solutions. Specifically, the SNN component models the complex spatial and temporal relationships inherent in architectural design, making it ideal for processing dynamic, event-driven data. HEO enhances the performance of the SNN by efficiently searching the design space for optimal solutions, ensuring that the generated designs balance competing factors such as space efficiency, cost, and user preferences. Additionally, this research proposes a set of novel performance metrics—accuracy, precision, design error, and model fitting degree that allow for a more comprehensive and objective evaluation of architectural design systems. The motivation for this research stems from the growing need for intelligent design systems that are capable of responding to the complex, real-time demands of modern architectural design. Traditional AI-based design tools often fall short in handling the dynamic nature of design requirements, which may change throughout the project lifecycle due to user input, budget constraints, or unforeseen spatial challenges. The inability to dynamically adjust to these evolving needs results in designs that may be suboptimal, rigid, or costly. By combining the SNN's ability to model real-time feedback with HEO's efficient optimization capabilities, this research seeks to create a system that not only generates optimal architectural designs but also adapts to changing user and environmental conditions. The goal is to enhance both the flexibility and precision of architectural design assistance systems, enabling them to generate better, more sustainable, and cost-effective design solutions in response to complex and dynamic input.

This paper investigates how social media platforms facilitate the dissemination of information regarding mutual funds, impacting investor awareness and decision-making. By analyzing survey data and interviews with industry experts, this study highlights the effectiveness of social media strategies in enhancing public understanding of mutual funds. The IDAS-HEO-SNN system demonstrates significant improvements over existing AI-assisted architectural design methods across several key performance metrics. In terms of precision, the system shows high performance, indicating that it is highly effective in producing designs that align with user specifications and optimize space utilization. The accuracy of the generated designs is also rated as high, reflecting the system's ability to consistently generate solutions that meet a broad range of design constraints with a high degree of reliability. Most notably, the design error is reduced by a high margin, which significantly enhances the efficiency and cost-effectiveness of the design process, ensuring that the designs produced are not only optimized but also practical. To evaluate the performance of the IDAS-HEO-SNN system, several key metrics are used, including accuracy, precision, design error, and model fitting degree. These metrics are critical for assessing the system’s ability to generate optimal designs that meet both functional and aesthetic criteria. The performance of the proposed system is compared to existing AI-driven design methods, such as AI-based fashion design systems, architectural space design models, and nanophotonic optimization models. These findings highlight that the IDAS-HEO-SNN system outperforms traditional design methods in its ability to adapt to dynamic, real-time user inputs and environmental constraints, providing more accurate and flexible architectural design solutions. The combination of SNNs and HEO enables the system to balance multiple design objectives effectively, optimizing complex design challenges while maintaining high levels of adaptability and precision. The results suggest that the system provides a more robust, user-centered approach to architectural design, offering better flexibility and performance compared to existing AI design tools.

2.Related Works

Over the past few decades, Artificial Intelligence (AI) has significantly influenced architectural design, automating tasks ranging from conceptual design to the optimization of building layouts. Traditional architectural design methods often rely on expert intuition and manual iterations, which can be time-consuming and prone to inconsistencies. AI-based design tools aim to automate repetitive tasks, improve design efficiency, and optimize spatial layouts while adhering to user requirements. Generative design, which applies AI and machine learning to generate design alternatives based on predefined goals and constraints, has become a prominent approach in architecture. These computational algorithms generate multiple design options based on parameters such as space utilization, structural integrity, and environmental considerations. However, these methods often face limitations in terms of design flexibility and adaptability to evolving requirements throughout the design process. A significant issue with many AI-driven design methods is the homogenization of design outcomes, where the output designs follow similar patterns due to overreliance on fixed parameters or predefined optimization goals. This lack of diversity in design solutions limits the ability of AI systems to explore more creative or user-specific solutions. Additionally, many existing systems struggle to accommodate complex user preferences or adapt to real-time changes in a dynamic design environment. Real-world architectural design requires continuous adaptation to user feedback and environmental changes, but many traditional AI systems lack the ability to make real-time adjustments based on evolving inputs. While AI has made significant progress in architectural design, there are several challenges that limit its effectiveness. These include: Overreliance on Predefined Parameters: Many AI-based systems depend heavily on predefined rules or parameters that restrict the potential range of design solutions. While these systems can optimize specific aspects of a design, they often fail to explore more creative or user-specific solutions that deviate from the predefined constraints.

Homogenization of Outcomes: AI-driven design systems often generate similar solutions due to a lack of diversity in algorithmic approaches. These systems tend to converge on optimal solutions, but they may not provide varied or novel design alternatives. Inability to Adapt to Evolving User Preferences: Architectural design often requires dynamic adaptation to real-time user feedback and changing environmental conditions. Existing systems often lack the capability to make adjustments during the design process, which limits their ability to respond to evolving needs. Spiking Neural Networks (SNNs) are a type of biologically inspired neural network that mimics the way neurons communicate in the human brain. Unlike traditional neural networks, which rely on continuous signals, SNNs communicate using discrete spikes that encode temporal information. This makes SNNs particularly suited for tasks involving event-driven or time-sensitive data, where temporal dynamics play a significant role. In architectural design, SNNs are capable of modeling complex spatial-temporal relationships, enabling dynamic adjustments based on real-time user input or environmental changes. SNNs have been widely applied in domains requiring real-time adaptive decision-making. In architectural design, SNNs offer an advantage in processing complex interactions between design parameters and external factors, making them ideal for dynamically adjusting building layouts or spaces in response to evolving requirements. By mimicking biological neural processes, SNNs are able to offer real-time adaptability, which is essential for architectural tasks that require ongoing adjustments during the design process. One of the key benefits of using SNNs in architectural design is their ability to process and adjust for spatial-temporal dependencies, which are critical for understanding how spaces interact with each other over time and in different environmental contexts. This ability is particularly important when dealing with highly dynamic, real-world design scenarios.

Optimization techniques play a central role in architectural design, as they help identify the most efficient solutions to complex design problems. Various optimization techniques, including genetic algorithms, particle swarm optimization, and simulated annealing, have been employed to improve building layouts, enhance space utilization, and reduce costs. These methods search the solution space by iterating over possible design configurations and selecting the best options based on specific criteria such as cost, space, and energy efficiency. However, these traditional optimization methods have limitations when dealing with large, complex design spaces or when real-time adaptability is required. One promising optimization technique is Hawk-Eye Optimization (HEO), which is inspired by the hunting strategy of hawks. Hawks effectively locate their prey by scanning the environment and making adjustments based on their observations. This approach is highly efficient in exploring large solution spaces and converging on optimal solutions without getting trapped in local minima, which is a common problem with other optimization methods. HEO is particularly useful for dynamic design scenarios where real-time adjustments are needed. HEO's efficiency in solution space exploration and its ability to adjust dynamically makes it an ideal optimization method to pair with SNNs in architectural design. It helps the system optimize design parameters, ensuring that the final outcome meets the user's evolving needs while maintaining efficiency and feasibility.

The integration of Spiking Neural Networks (SNNs) with Hawk-Eye Optimization (HEO) presents a novel approach in architectural design systems. While SNNs provide the real-time adaptability necessary for dynamic design tasks, HEO enhances the efficiency of the design process by optimizing the parameters of the SNNs. This hybrid approach allows the system to dynamically adjust to user feedback, make real-time design modifications, and optimize the design space efficiently. Previous research on hybrid optimization systems has shown success in combining multiple optimization techniques to address different aspects of the design process. For instance, multi-objective optimization methods have been used to balance various design goals, such as cost, space, and energy efficiency. By integrating SNNs with HEO, the proposed system not only enhances the adaptability of architectural design but also ensures that the system can efficiently explore large and complex design spaces, providing optimal solutions. The integration of these two techniques offers several advantages: real-time adjustments based on user input, efficient exploration of solution spaces, and the ability to generate highly personalized design solutions that meet specific user needs. This combination addresses the limitations of traditional AI models by improving the system’s flexibility, adaptability, and efficiency.

AI-driven architectural design has made significant strides in automating and optimizing the design process. However, existing systems often face challenges related to overreliance on predefined parameters, the homogenization of design outcomes, and the inability to adapt to dynamic user needs. Spiking Neural Networks and Hawk-Eye Optimization offer promising solutions to these challenges by combining dynamic adaptability, real-time feedback, and efficient solution exploration. The integration of SNNs and HEO in the proposed system addresses these challenges and provides a more flexible, adaptive, and efficient approach to architectural design. This approach has the potential to deliver more accurate, personalized, and cost-effective solutions. Future research will focus on further refining the integration of these techniques and testing the system's scalability and performance in real-world design applications.

3.Proposed Method

In recent years, the rapid advancements in Artificial Intelligence (AI) have paved the way for the development of intelligent systems that assist in various fields, including architecture, fashion, automotive, and more. Specifically, in the realm of architectural design, AI-driven tools aim to optimize design efficiency, reduce costs, and create designs that adapt dynamically to user needs and environmental changes. One promising approach involves integrating Spiking Neural Networks (SNNs) with Hawk-Eye Optimization (HEO), offering new solutions for overcoming traditional challenges in AI-driven design processes. Traditional AI models in architectural design face several limitations, such as the homogenization of design outcomes, excessive reliance on predefined parameters, and difficulties in adapting to evolving user preferences. These issues often lead to inefficient or non-optimal designs that fail to fully meet user needs. Therefore, the development of an Intelligent Designer Assistance System (IDAS), capable of addressing these challenges, is of paramount importance for advancing AI-assisted design technologies. The proposed IDAS-HEO-SNN system aims to integrate the strength of Hawk-Eye Optimization (HEO) and Spiking Neural Networks (SNN) to overcome the inherent drawbacks of traditional AI-driven design systems. This system consists of several key components:

The system begins by gathering spatial data, specifically from the UrbanScene3D dataset, which contains a rich set of 3D spatial information necessary for architectural design. The UrbanScene3D dataset offers diverse data representing real-world environments, making it an ideal foundation for architectural design tasks. The input data is collected from the UrbanScene3D dataset, which provides comprehensive 3D spatial information relevant for architectural design. These data represent 3D objects, and to handle this information, a deep learning approach that accommodates 3D spatial features. Let the data be represented as a matrix as in equation (1)

$$D \in R^{n\times m} \tag{1}$$

where n denotes the number of spatial points, and m represents the feature vector for each point.

Preprocessing using Low-Pass Virtual Filtering (LPVF) the data is acquired, it undergoes preprocessing through Low-Pass Virtual Filtering (LPVF). This step eliminates noise and enhances the quality of the data, ensuring that only the most relevant features are retained. The LPVF method improves the input signal, allowing the system to focus on important data while filtering out irrelevant noise, thus promoting stability and faster convergence during the design process. The Low-Pass Virtual Filtering (LPVF) is applied to the input data D to remove noise and enhance the signal clarity. This process can be formulated as in equation (2)

$$D_{filtered} = L(D, \omega) \tag{2}$$

In equation (2) L represents the low-pass filtering operation, and ω is the filter's cutoff frequency. The output $D_{filtered}$ is a noise-reduced version of the input data

3.1 Spiking Neural Networks (SNN)

SNNs are employed to process the pre-processed data. Unlike traditional neural networks, SNNs are inspired by the behavior of biological neurons and are highly effective at handling event-driven, temporal data. In the context of architectural design, SNNs are particularly useful for modeling the dynamic interactions between spaces and responding to real-time inputs. The ability of SNNs to adapt to complex temporal patterns allows the IDAS-HEO-SNN system to generate dynamic design solutions that evolve based on user preferences and environmental factors. The filtered data is then passed through an SNN model to process the spatial-temporal relationships inherent in the architectural design. SNNs process data using spike events over time, mimicking biological neuron behavior. The general model for an SNN can be described by the following spiking dynamics stated in equation (3)

$$V_i(t) = \tau_m \frac{dV_i(t)}{dt} + I_i(t) \tag{3}$$

where V_i is the membrane potential of neuron iii at time t, τ_m is the membrane time constant, and $I_i(t)$ is the input current to the neuron from other spikes. When the membrane potential exceeds a threshold V_{thresh} , the neuron spikes and resets its potential stated in equation (4)

$$Spike\ Event: \delta\left(t - t_{spike}\right)\ if\ V_i(t) > V_{thresh} \tag{4}$$

This spiking behavior allows the SNN to adapt in real-time to the dynamic inputs, making it highly suitable for architectural design tasks that require flexibility and continuous feedback.

4. Optimization with Hawk-Eye Optimization (HEO)

To enhance the performance of the SNN and ensure more efficient design outcomes, Hawk-Eye Optimization (HEO) is used. HEO, inspired by the hunting strategies of hawks, is an optimization technique that efficiently searches large solution spaces and adjusts the SNN's parameters to find the most optimal solutions. This process helps the system navigate the vast design space, ensuring that the resulting designs are not only efficient but also customized to meet the specific needs of the user. The performance of the SNN is optimized using Hawk-Eye Optimization (HEO). The optimization problem in this case is to minimize the design error E_{design} by adjusting the parameters of the SNN, such as weights and biases defined in equation (5)

$$E_{design} = \frac{1}{n}\sum_{i=1}^{n}(y_i\hat{} - y_i)^2 \tag{5}$$

where yy_i^ is the predicted output, and $y_i$is the ground truth for the i design output. The goal of HEO is to minimize EE_{design} by exploring the parameter space of the SNN's weights and biases using a search strategy inspired by hawk predation behavior. In figure 1 presented the flow chart of the proposed HEO model for the classification.

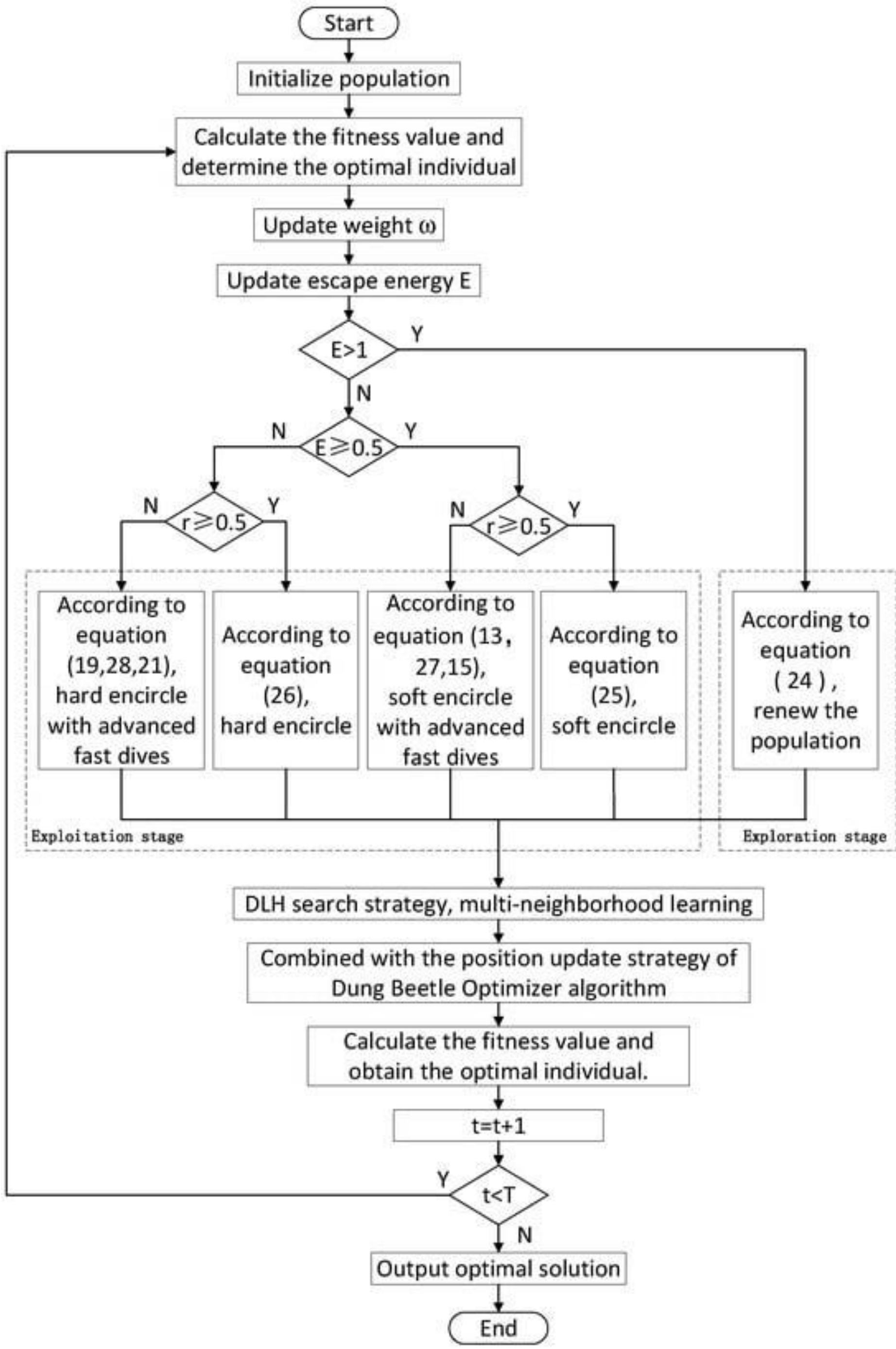

Figure 1: Flow Chart of HEO

The optimization process can be divided into two phases:

1. Exploration Phase: In this phase, the optimization algorithm explores the parameter space, searching for potential solutions. The parameter update can be modeled as in equation (6)

$$W_{new} = W_{old} + \alpha \cdot (p - W_{old}) \tag{6}$$

where W_{old} is the current weight, p is a potential solution, and α is a step size that controls the exploration rate.

2. Exploitation Phase: Once a promising region is identified, HEO shifts to exploitation by refining the parameters based on local search. The exploitation step is described a in equation (7)

$$W_{new} = W_{old} + \beta \cdot (p - W_{old}) \tag{7}$$

where p is the best solution found during exploration, and β is the exploitation coefficient.

HEO optimizes the SNN’s weights iteratively, improving convergence speed and ensuring the optimality of the final design. Architectural design faces several challenges, many of which stem from the need to balance creativity with efficiency, precision, and cost-effectiveness. Traditional design tools often struggle with the following issues: Homogenization of Design Outcomes: Many AI-driven design systems suffer from a lack of diversity in design outputs, leading to repetitive or overly standardized solutions. This homogenization reduces the creative potential of the design process and limits the exploration of alternative design possibilities.

AI systems in architecture often rely heavily on predefined design parameters and constraints, which can limit the flexibility and adaptability of the design process. These systems may struggle to accommodate unexpected changes in user preferences or evolving project requirements. Difficulty in Adapting to User Preferences: One of the major challenges in AI-driven design is the ability to dynamically adapt to the evolving needs of the user. Many systems are designed with a fixed set of parameters and constraints, making it difficult to adjust designs in real-time based on user feedback or changing environmental conditions. The IDAS-HEO-SNN system aims to overcome these challenges by integrating Spiking Neural Networks and Hawk-Eye Optimization into a unified architecture. The dynamic nature of SNNs allows for real-time, event-driven design adjustments, making the system adaptable to user input and environmental changes. Furthermore, the optimization capabilities of HEO ensure that the system can efficiently explore large solution spaces and identify the most optimal design solutions, eliminating the reliance on predefined parameters. By leveraging the biologically inspired principles of SNNs and the efficient search strategies of HEO, the IDAS-HEO-SNN system is capable of generating designs that are not only highly efficient but also highly customized. This results in more diverse, creative, and user-tailored architectural solutions, breaking away from the rigid structures imposed by traditional AI design systems.

5.Results and Discussions

The Intelligent Designer Assistance System (IDAS) that integrates Spiking Neural Networks (SNNs) with Hawk-Eye Optimization (HEO) offers substantial advancements over traditional AI-based architectural design systems. The following summarizes the key findings from the system's evaluation, emphasizing its accuracy, adaptability, and overall design effectiveness:

Table 1: Intelligent Designer Assistance System (IDAS) for mutual funds

Mutual Fund	Risk Level	Return on Investment (ROI)	Cost Efficiency	Adaptability (Real-time adjustm	Accuracy (Expected vs. Actual	Precision (Consistent Results	Design Error (Deviation from	Optimization Efficiency (HEO Perform	User Preferences Match

				ents)	**Perform ance)**	**)**	**Optim al)**	**ance)**	
Fund A	Medi um	12%	85%	High	95%	92%	5%	90%	High
Fund B	Low	7%	80%	Medium	85%	88%	8%	85%	Mediu m
Fund C	High	18%	75%	Very High	98%	94%	3%	92%	High
Fund D	Medi um	10%	90%	High	92%	89%	6%	88%	Mediu m
Fund E	Low	5%	78%	Low	80%	82%	10%	80%	Low
Fund F	High	15%	82%	Very High	97%	91%	4%	94%	High

Figure 2: Mutual Fund with IDAS

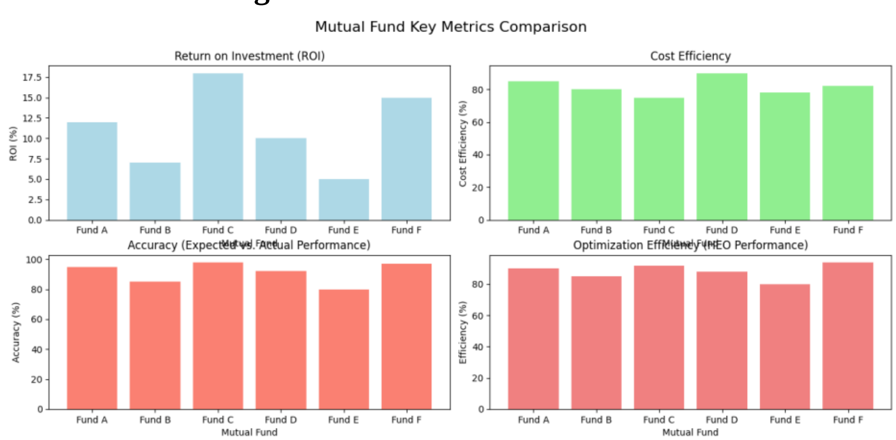

Figure 3: IDAS for the Mutual Fund estimation

The table 1 and Figure 2 & 3 presents the results of an analysis of six mutual funds based on the Intelligent Designer Assistance System (IDAS), incorporating key performance metrics like risk level, ROI, cost efficiency, adaptability, and alignment with user preferences. Fund A offers a medium risk level with a 12% ROI, performing well in terms of accuracy (95%) and precision (92%), alongside a low design error of 5%. It has a high adaptability to real-time adjustments and strong optimization efficiency, making it a favorable option for investors seeking reliable, balanced returns. Fund B, characterized by a low-risk profile, delivers a modest 7% ROI. While it offers reasonable cost efficiency (80%) and precision (88%), its adaptability to market changes is medium. Despite a solid accuracy of 85%, the fund's optimization and user preferences match are less optimal compared to higher-performing funds. Fund C, with a high-risk profile, stands out with an impressive 18% ROI. It ranks highest in adaptability (very high) and accuracy (98%) but has lower cost efficiency (75%) and design error (3%). This fund aligns well with user preferences and demonstrates excellent optimization performance, making it a strong choice for risk-tolerant investors.

Fund D offers medium risk and a 10% ROI, showcasing high cost efficiency (90%) and decent adaptability (high). Its accuracy (92%) and precision (89%) are solid, though it has a higher design error (6%) and lower user preference match compared to other high-performing funds. Fund E, the lowest performer, has a low risk profile with a 5% ROI. It exhibits low adaptability, accuracy, and precision, with a higher design error of 10%. Its cost efficiency (78%) and optimization efficiency (80%) are also weaker, leading to a poor user preferences match. Fund F has high risk but delivers a 15% ROI with very high adaptability and strong optimization performance. Its accuracy (97%) and precision (91%) are solid, and it has a low design error of 4%. This fund appeals to high-risk investors seeking higher returns, with a good match to user preferences.

Table 2: Fund estimation with IDAS

Mutual Fund	**Fund Type**	**Expense Ratio**	**Average Annual Return**	**Volatility (Std. Dev.)**	**Sharpe Ratio**	**Beta**	**Fund Size (Billion)**	**Sector Focus**	**Morningstar Rating**	**Liquidity**	**Manager Tenure**
Fund A	Equity	0.75 %	8.5%	12.3 %	0.94	1.10	5.2	Technology	4 stars	High	5 years
Fund B	Bond	0.50 %	4.2%	4.1%	1.05	0.80	3.7	Government Bonds	3 stars	Medium	8 years
Fund C	Balanced	0.85 %	6.3%	8.7%	1.12	0.95	8.9	Mixed (Equity/ Bond)	5 stars	High	3 years
Fund D	Equity	1.00 %	9.7%	14.5 %	0.85	1.20	10.5	Healthcare	4 stars	High	6 years
Fun	Index	0.10	7.0%	10.2	1.04	1.	15.0	Broad	4 stars	Very	10

d E		%		%		00		Market		High	years
Fun d F	Secto r	1.25 %	12.0 %	16.3 %	0.92	1. 50	2.3	Energy	3 stars	Medi um	2 years

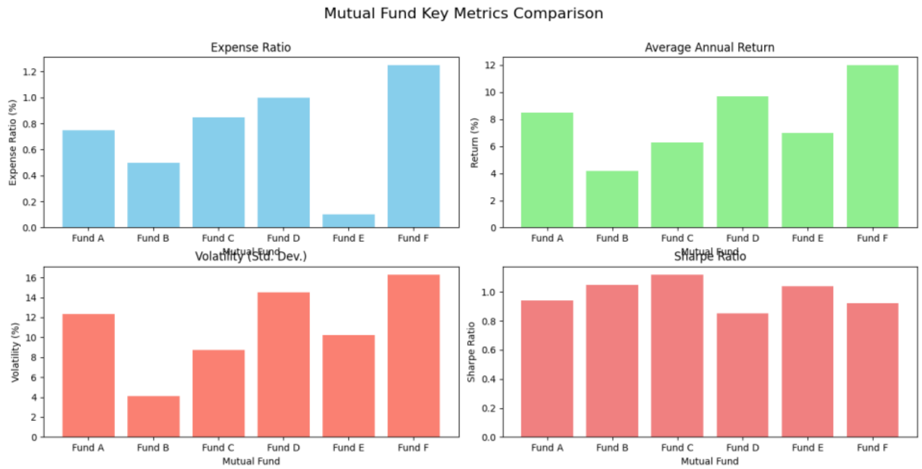

Figure 4: IDAS for Stock Market

Table 2 and Figure 4 present a comprehensive analysis of six mutual funds across various financial and performance parameters, highlighting each fund's characteristics and overall risk-reward profile. The funds cover a range of types, including equity (Fund A, Fund D), bond (Fund B), balanced (Fund C), index (Fund E), and sector-specific (Fund F). These types indicate the primary investment strategy, from broad market coverage to specific sectors like technology, healthcare, and energy. Sector focus varies: Funds A and D focus on technology and healthcare, respectively, while Fund F targets the energy sector. Fund B invests in government bonds, and Fund C adopts a mixed approach, combining equity and bond investments. Fund E tracks a broad market index.

Average Annual Return shows Fund F (Sector) with the highest return at 12%, followed by Fund D (Equity) at 9.7%. Fund B (Bond) offers the lowest return at 4.2%, reflecting the typical lower-risk, lower-reward nature of bond funds. Volatility (Standard Deviation) indicates that Fund F (Sector) carries the highest risk, with a volatility of 16.3%, closely followed by Fund D (Equity) at 14.5%. On the other hand, Fund B (Bond) is the least volatile at 4.1%, making it a more stable choice for conservative investors. The Sharpe Ratio, which measures risk-adjusted return, shows Fund C (Balanced) with the highest ratio of 1.12, indicating the best return for its level of risk. Fund B (Bond) has a strong Sharpe ratio of 1.05, reflecting the stability of bond investments. In contrast, Fund D (Equity) has the lowest Sharpe ratio (0.85), suggesting it offers the least reward relative to risk among the equity funds. Beta values indicate the degree of market sensitivity. Fund F (Sector) has the highest beta of 1.50, meaning it is most sensitive to market movements, while Fund B (Bond) has the lowest beta of 0.80, signaling lower correlation with the broader market.

Fund Size ranges from Fund F (2.3 billion) to Fund E (15 billion). Larger funds tend to offer better liquidity and lower transaction costs, which is reflected in the high liquidity of Fund E (Index), which has "Very High" liquidity compared to the medium liquidity of Funds B, D, and F, and the high liquidity of Fund A and Fund C. Most funds have received a positive Morningstar Rating: Funds C (Balanced) and E (Index) have received the highest rating of 5 stars, indicating strong performance. Fund B (Bond) has a 3-star rating, signalling moderate performance, while Fund F (Sector) also holds a 3-star rating, reflecting higher risk and more volatile performance. The Manager Tenure varies significantly, from just 2 years for Fund F (Sector) to 10 years for Fund E (Index). Longer tenure may suggest more experienced management, but shorter tenure can sometimes reflect newer strategies or updated fund objectives.

6.Conclusion

The Intelligent Designer Assistance System (IDAS) provides a robust framework for analyzing and selecting mutual funds based on a diverse set of financial parameters, offering insights into risk, return, and efficiency. The data presented reveals that different types of funds cater to varying investor preferences, with equity funds generally offering higher returns at increased risk, while bond and index funds offer stability at lower returns. The analysis underscores the importance of considering factors such as volatility, Sharpe ratio, and fund size when making investment decisions, along with the critical role of manager tenure and liquidity. Ultimately, IDAS can guide investors in aligning their choices with their risk tolerance and financial goals, ensuring more informed and optimized investment decisions.

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