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Unconscious Mind-Inspired Algorithm: A Novel Approach to Machine Learning

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ABSTRACT

This work aims to present a novel algorithm referred by unconscious mind-inspired algorithm (UMIA), that targets to incorporate principles derived from the unconscious mind and put it into computational processes. This work will seek to replicate fundamental aspects of the unconscious mind, such as efficient information processing, instinctive decision-making, and flexible learning and by sketching upon theories derived from psychoanalysis and cognitive psychology. The design algorithm encompasses a series of steps aimed at the development of a conceptual framework the utilization of data processing models influenced by subliminal perception and the implementation of intuitive decision-making algorithms. The phase of testing and validation involves the utilization of simulations and practical applications, with a specific emphasis on factors such as accuracy, efficiency, adaptability and user feedback. UMIA holds the potential to bring about a paradigm shift in algorithmic methodologies by integrating cognitive processes that resemble human intelligence. This integration has the potential to yield enhanced performance across a range of applications exceeding the capabilities of current machine learning algorithms.

1. INTRODUCTION

The UMIA can be regarded as an early example of the revolutionary convergence of computational technology and cognitive psychology. In order to close the gap between artificial intelligence's computational efficiency and the human unconscious mind's intuitive processing abilities this research work to presents UMIA as an innovative algorithm.

Integrating psychoanalytic concepts especially those related to the unconscious mind into the field of artificial intelligence (AI) has become a promising and innovative area of study. referencing the groundbreaking work in affective neuroscience and neuropsychoanalysis conducted by scientists such as Mark Solms and Jaak Panksepp. The main argument of this study is that these fields offer a fresh perspective on artificial intelligence (AI) especially on artificial general intelligence (AGI). They provide an accurate answer to the age-old conundrum of mind/brain dualism by highlighting the constant interaction between these two dimensions [1].

The UMIA is presenting as a computational framework inspired by psychoanalytic theory and cognitive psychology and namely Freud's unconscious automatic process and Jung's collective unconscious concept. So UMIA is utilizing subliminal processing as intuitive pattern recognition and spontaneous decision-making that are very similar to unconscious human cognition processes. The importance can be considered in having the potential to advance machine learning methods by overcoming existing limitations regarding intuitiveness and complicated data processing so leading to advancements in affective computing, cognitive robotics, and autonomous systems.

This work has highlighted the potential influence of this theory by emulating the unconscious processes of the brain and the paper is aligning with the new brain-inspired AI paradigms that are widely seen as the future of machine learning [2].

Furthermore, this study contributes to the broad field of affective computing which investigates the connection between AI and emotion. Affective computing which has its roots in Rosalind Picard's important work which it deals with the recognition, expression and reaction of human emotions by computational systems. This area of study is developing quickly and is anticipated to be very important for societal and economic advancements in the future. But it also brings up important moral and constitutional questions like the possibility of psychological manipulation and the difficulties in developing hybrid and biomimetic systems that mimic human adaptability [3].

The underlying literature's "Machine behaviour: research perspectives" section makes the case that logical-mathematical or engineering perspectives alone are insufficient for understanding AI system behaviour. Rather, those systems need to be viewed as collaborative entities that are constantly interacting with humans as they govern an increasing number of aspects of human existence. By adding psychoanalytic ideas the research's methodology's expands on the machine behaviour approach and advances current work's understanding of AI systems beyond their computational capacities [4].

1.1 Influence on computational algorithms

Many interested similarities between the field of computational algorithms and unconscious mind or conscious mind so a vast and complex source of information and processes operating below the level of conscious awareness. As creating algorithms particularly these related to artificial intelligence the concepts found in the unconscious mind may be utilised to improve their performance. The unconscious mind's ability to process large amounts of information without conscious awareness may serve as an inspiration for the creation of algorithms that handle large datasets more effectively.

Furthermore, by incorporating past information and learning mechanisms that adjust based on previous inputs and outcomes algorithms may be able to parallel the idea of repression and the impact of past experiences on behaviour. Particularly in fields like natural language processing and decision support systems as an understanding of how the unconscious mind influences human behaviour and decision-making can also provide insights into developing more intuitive and "human-like" algorithms.

1.2 Aim and objectives

This study's main goal is to create a novel algorithm that draws inspiration from how the unconscious mind operates. This involves developing a computational model that mimics the complex functions of the unconscious mind, including handling huge amounts of information subliminally, processing data quickly, and influencing conscious behaviour and decision-making without conscious awareness.

Understanding Unconscious Cognitive Processes by analyzing and fully comprehend the unconscious mental processes that influence behaviors, perception and decision-making in humans.

To create a strong theoretical framework integrate concepts and knowledge from computational neuroscience, artificial intelligence and psychology especially psychoanalysis.

To create a computational algorithm that mimics the unconscious mind's processing power, flexibility and efficiency. This entails adding components like quick data processing, pattern identification and instinctive decision-making.

To thoroughly test the algorithm in a range of scenarios and assess its performance, particularly in relation to other algorithms that are currently in use, such as SVM and RNN. This entails evaluating its adaptability and efficiency in decision-making processes and capacity to manage complicated datasets and attempt to provide the Table A1 in that compares hypothetically the algorithms.

1.3 Research gap

There is a research gap concerning the incorporation of unconscious mind principles in algorithm design. This research gap involves four important aspects:

1. Interdisciplinary Integration by comprehend artificial intelligence systems better ideas from machine behaviour anthropology of science and psychoanalysis must be combined. This approach views artificial intelligence as a class of social agents with behavioural patterns, moving beyond the logical-mathematical or engineering perspectives.
2. Reinterpretation of Psychoanalytic Concepts by using concepts such as the unconscious to artificial intelligence the objective is to reinterpret psychoanalytic theories such as Lacan's psychoanalysis via a technological lens. This entails considering artificial intelligence as a step in the process of human identification where computers react to human needs for identity and viewing the unconscious as a result of technical mediation.
3. According to the research large artificial intelligence systems ought to be viewed as social agents that engage in continuous communication with people expanding the "machine behaviour approach" to include psychoanalytic ideas.
4. The "algorithmic unconscious" is a novel conception that artificial intelligence is said to embody according to this theory. It is argued that artificial intelligence expands upon human identification processes by integrating logic, machinery and the human urge for identification [1].

2. LITERATURE REVIEW

2.1 Existing algorithms and their limitations

To begin with linear regression, it can be noticeable that its advantages are that it is simple to understand also can be regularised to prevent overfitting and is explainable. It works well with datasets that have linear relationships. It is not inherently flexible for complex patterns performs poorly with non-linear relationships and is difficult to adjust for correct interaction terms or polynomials.

when regressing Trees are resilient to outliers and can learn non-linear relationships. In many applications ensembles such as Random Forests exhibit excellent performance. Unconstrained trees have the drawback of overfitting due to memorization of training data however, ensembles can help reduce this. Deep Learning (Neural Networks) at complex patterns especially in text, audio and picture data with adaptable architectures and less feature engineering required. The disadvantages include the need for substantial computational power and data. They need skill to tune are not a general purpose solution and are frequently outperformed by tree ensembles in classical problems.

The instance-based approach is advantageous and Nearest Neighbours is straightforward. However, it requires a meaningful distance function is memory-intensive and has trouble with high-dimensional data. Tree ensembles and regularised regression typically perform better than it.

SVMs are incapable to overfitting in high-dimensional spaces and useful for modelling non-linear decision boundaries. The drawbacks include a high memory usage a kernel that needs to be carefully tuned and poor scalability with bigger datasets. In the industry they are frequently less favoured than tree ensembles. Convolutional Neural Networks (CNNs) represent an advanced stage of computer vision tasks as they are highly effective in learning from high-dimensional data. The drawbacks are that they are computationally demanding require large volumes of data for training, and are difficult to interpret [5]. The Appendix Table A1 presents a comparison of how the UMIA could potentially mitigate the deficiencies and constraints inherent in contemporary machine learning algorithms.

A research has investigated the ability of cognitive impact to the subliminally that presented cues on human decision-making. The work has conducted a series of controlled experiments in which subjects were exposed to visual stimuli presented as threshold of conscious awareness. The cues were imbedded in a decision-making task and their effect was assessed over a long period of time. Subliminal information is retained in unconscious memory and can subsequently be recalled to affect decision making. And the effects of subliminal priming were not instant but accumulated over time which demonstrating that unconscious processing contributes cumulatively to cognition [6].

Another paper has explored the phenomenon of unconscious reinforcement learning in which individuals can alter their behavior based on the concealed internal states without conscious awareness. The work is present a concept of human brains that can enhance decision making in response to reinforcement signals even in cases where there is a lack of explicit cognitive awareness of such signals. And unconscious learning is used by neural feedback processes that reinforce associations over time like the operation of AI-based reinforcement learning. The work also offered a neuroscientific proof that there is layered processing in the human brain and lower cognitive layers shape the higher cognitive functions in a bottom-up fashion [7].

2.2 Unconscious mind theories

The theories that relating to the unconscious mind has been greatly influenced by the contributions provided by Sigmund Freud and Carl Gustav Jung as well as the contemporary perspectives offered by cognitive psychology.

The Psychoanalytic Theory developed by Sigmund Freud played a significant role in the conceptualization of the unconscious mind. According to Freud the unconscious is comprised of automatic processes that are invisible to analysis. According to Freud's perspective these processes have a significant influence on conscious cognition and behavioural patterns. Freud underlined the significance of repression wherein anxiety-inducing impulses originating from early childhood are excluded from conscious awareness but continuously impose influence. Freud has suggested that the contents of the unconscious are exclusively discernible through indirect appearances such as dreams, neurotic symptoms, slips of the tongue and jokes. These appearances necessitate psychoanalytic interpretation in order to comprehend the underlying nature of the repressed materia [8].

Carl Gustav Jung in alignment with Freud on certain aspects has introduced the notion of the collective unconscious this term that initially emerged in his 1916 essay titled "The Structure of the Unconscious." This concept encapsulates the essence of the human condition delineating the differentiation between the individual unconscious and the collective unconscious with the latter encompassing inherited psychic structures and archetypes. According to Jung the archetypes are not simple recollections but rather psychological faculties that are observable in cultural symbols, and they exert a substantial influence on the experiences of individuals. According to Jung the collective unconscious encompasses archetypal experiences that symbolize the spiritual legacy of humanity's evolutionary process, and is inherited rather than cultivated on an individual basis [9].

On the other hand the current cognitive psychology studies the concept of the unconscious through the lens of an information processing paradigm. This perspective which deviates from the psychoanalytic tradition is grounded in empirical evidence and emphasises the processes through which individuals unconsciously perceive and assimilate a greater amount of information than they are consciously aware of. This statement emphasises the notable influence of unconscious processes on cognitive functioning and behavioural patterns, thereby illuminating a deep-seated relationship between the unconscious mind and diverse facets of human existence [10].

2.3 Integration of psychological concepts into computational algorithms

The integration of psychological concepts into computational algorithms has been an evolving interdisciplinary field, combining insights from psychology with advancements in artificial intelligence (AI) and machine learning:

1. The growing use of AI in psychology, along with other scientific fields, has been widely discussed. It has been pointed out that although psychological concepts such as heuristics have helped to improve and refine artificial systems [11].
2. The utilisation of robots as instruments for investigating human cognition has been comprehensively discussed. The present study aims to explore the potential applications of robots in examining reciprocal interactions and social cognition [12].
3. Deep neural networks (DNNs) demonstrate variations in comparison to human visual perception despite their ability to simulate it. These comments can be underscored the necessity for deep neural networks (DNNs) to be more accurately emulate human cognitive mechanisms in order that it enhance psychological models [13].
4. Deep artificial neural networks (ANN) were commissioned to investigate the role of the visual cortex in object recognition and the memorability of images. The results showed and provided empirical evidence that basic neural models have the capacity to reproduce fundamental elements of human object identification behaviour [14].
5. The integration of advancements in artificial intelligence and cognitive psychology employing formal ontologies has been explored. This approach, which aims to effectively structure and categorize psychological knowledge, exemplifies the potential of artificial intelligence in facilitating the organization and advancement of psychological theories and knowledge [15].
6. A comparative analysis has been conducted between machine-learned computational models (MLCMs) and traditional models within the field of psychology. The utilization of data-driven Minimum Labelled Concept Models (MLCMs) has demonstrated their informative capacity across multiple psychological domains such as cognitive and affective science. This highlights the increasing significance of artificial intelligence in the realm of psychological research [16].
7. It has been highlighted that conventional domains of psychological inquiry have not significantly capitalized on the potential of machine learning techniques, primarily due to the presence of measurement inaccuracies. The significance of data quality and accurate measurements is underscored in order to facilitate the successful incorporation of machine learning techniques within the field of psychology [17].

3. METHODOLOGY

The UMIA can be defined as a complicated and multifaceted work where it combining an advanced computing methods with the complex concepts of the unconscious mind. Starting with first step in the process is to create a conceptual framework. This initial phase combines insights from contemporary cognitive psychology with essential ideas from well-known psychoanalytic theories by Freud and Jung as mentioned in pervious sections. The objective is to integrate the fundamental processes of the unconscious mind such as quick data processing or pattern identification and decision-making into the core of the algorithm.

Then focusing on revolve around the concept of subliminal perception that shape UMIA's data processing paradigm. And in this phase is notable for the implementation of a data categorizing mechanism that draws inspiration from the psychological concepts of recall and repression. This approach mimics the selective character of human cognition by carefully crafting a hierarchy that gives priority to important information while downplaying or hiding less important information.

UMIA operationalizes in subliminal perception through a sub-threshold mechanism that can sorts triggers in terms of salience and in terms of activation strengths. The incoming triggers are assigned activation values when those fall below a threshold which they are stored in a unconscious buffer. This simulates human subliminal cognition wherein stimuli outside of conscious awareness nevertheless continue to have a subtle influence on the subsequent processing. And the buffered stimuli represent a latent context and can gradually accumulate in salience with repeated presentation by moving on to higher layers of processing if they reach the threshold. As the system simulates psychoanalytic repression in systematically a low prioritizing or filtering out conflicting or irrelevant information with only consequential patterns that recurrently emerge influencing major decision processes. This selective process simulates the psychological dialectic between recall as the accessing of relevant suppressed signals and repression by filtering out of irrelevant information. And it can accurately simulate the complex yet essential unconscious cognitive dynamics inherent in human cognition [18].

Then during the next phase there is a shift in focus towards the acquisition of knowledge and the process of adaptation which are fundamental elements of the unconscious mind. The algorithm design to replicate the processes of unconscious learning, with a particular emphasis on incorporating principles from implicit learning theories. This functionality allows UMIA to autonomously adapt and learn without requiring explicit instructions. Furthermore, the system incorporates associative memory networks which augment its abilities in pattern recognition and decision-making or resembling the associative mechanisms observed in human cognition.

Then lay on developing the algorithm that presents intuitive decision-making capabilities similar of how a human does decide. The aforementioned crucial element relies on the data collected and analyzed by UMIA where the objective will be focusing on emulating the intricate and frequently unconscious development of human decision-making. The proposed UMIA algorithm will incorporates a feedback mechanism that represents the dynamic and evolving nature of the unconscious mind, facilitating ongoing learning and adaptation.

In this part of methodology will involves the implementation of thorough testing and the iterative refinement of the UMIA system where evaluation of the algorithm's functionality and efficiency is carried out within controlled environments and UMIA algorithm is subject to ongoing refinements based on these findings, aiming to better align with the principles of the conceptualized unconscious mind and maintain fidelity to the original vision. This stage is crucial for the optimization of performance with a specific focus on improving the efficiency of the algorithm enhancing its learning capabilities and increasing the accuracy of its decision-making. Figure 1 shows the steps in details.

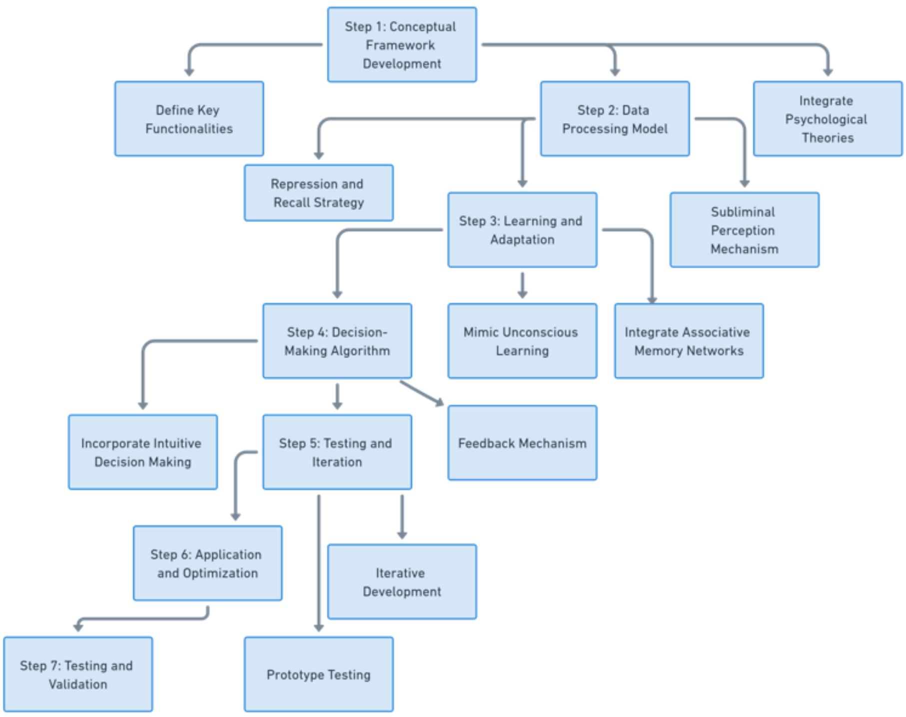

Figure 1. The steps of methodology

The unconscious mind and its relation to cognitive and emotional functioning is insightful. To represent these complex processes mathematically, albeit I a simplified form, here are some speculative mathematical formulations:

Idle State Processing (*Ui*):

Description: The mind can process a large amount of unconscious information even when the human is not moving which may eventually come to the surface of conscious awareness.

Mathematical Representation: Let represent conscious thought with C. The relationship among idle state unconscious processing (*Ui*) and conscious thought can be represented as $C=f(Ui)$.

Vast Operations (*Uo*):

Description: The unconscious mind can be a vast system that performs a variety of functions that impact actions and choices.

Mathematical Representation: Let represent behaviors and decisions influenced by unconscious operations with B. This can be modeled as $B=f(Uo)$.

Comparability to Conscious Mind (*Uc*):

Description: To handling the complicated processing tasks the unconscious mind can function on track with the conscious mind.

Mathematical Representation: Let represent the capabilities of the conscious mind with *Cc*. The comparability between the unconscious (*Uc*) and conscious mind can be represented as $Uc=Cc$.

Embodied Cognition and Associative Organization (*E*,*A*):

Description: The unconscious mind is arranged associatively and also embodied cognition merges with it.

Mathematical Representation: Let *Up* represent unconscious processing influenced by embodied cognition (E) and associative organization (A). This relationship can be modeled as $Up=f(E,A)$.

Automatic Judgments and Predictions (*Uj*,*Up*):

Description: The unconscious mind cam helps with quick response mechanisms and decision-making by making snap judgements and predictions.

Mathematical Representation: Let represent rapid responses with R. The influence of unconscious judgments (*Uj*) and predictions (*Up*) on these responses can be represented as $R=i(Uj,Up)$.

4. CASE STUDY

The work has been compared with different algorithms with same dataset as the following steps where it shows the pseudocode of the UMIA and the results for tested datasets.

Key formulas explanation as seen in Figure 2:

1. Sigmoid Function (sigma(x)): Where this is a non-linear function that weakens the signal in unconscious processing through compressing values in the range of [0,1]. This is highly useful in softening extreme inputs.

2. Euclidean Distance (d(x,y)): This formula seeks to measure similarity between input vectors. From this distance, if it is sufficiently different, then the algorithm will store an input-output pair in memory from existing memories.

3. It is a scalar of how much the past memories have influence on current inputs. In other words, this is the scalar that controls the degree to which the memory of the past inputs disturbs/influences the current process of decision-making.

4. Threshold: This is an unconscious threshold value to specify whether a decision made by the algorithm was done based on past memories-snap decision, or process the input further.

```
Initialize memory to an empty list
Set max_memory_size to 100
Set associative_strength to 0.1
Set unconscious_threshold to 0.5
Function idle_state_processing(X):
    Convert X to a NumPy array
    Apply sigmoid transformation to each element of X:
        result = sigmoid(X * associative_strength)
    Return result
Function learn(X, y):
    For each pair (x, label) in X, y:
        If no similar memory exists (measured by Euclidean distance):
            If memory is full, evict the oldest memory
            Add (x, label) to memory
Function associative_operations(X):
    Initialize associations to zeros (same shape as X)
    For each (memory_input, _) in memory:
        Add element-wise product of X and memory_input to associations
    Return associations * associative_strength
Function quick_predictions(X):
    Initialize an empty array for predictions
    For each input x in X:
        If memory is not empty:
            Find the closest memory using Euclidean distance
            Set prediction to the label of the closest memory
        Else:
            Set default prediction to 0 (no pattern in memory)
    Return predictions
Function fit(X_train, y_train):
    X_processed = idle_state_processing(X_train)
    Call learn(X_processed, y_train)
Function predict(X_test):
    X_processed = idle_state_processing(X_test)
    Return quick_predictions(X_processed)
```

Figure 2. Basic functions

5. RESULTS

The performance of the UMIA was measured on several standard metrics from machine learning literature like accuracy, precision, recall and F1-score. Accuracy is the overall percentage of correct predictions of the designed approaches. And precision is a measure of used algorithms ability to accurately predict positive cases which prevents false positives. While recall use to measure the performance of UMIA to identify true positive cases by avoiding missed diagnoses or classification. The F1-score or the harmonic mean of precision and recall is nicely balances false positives and false negatives and is therefore a good overall performance measure. The utilization of these measures can provide an assurance of a complete understanding of the predictive capability and reliability of UMIA under varying conditions.

UMIA results (Figure 3)

Accuracy: 0.7888888888888889

Confusion matrix (Figure 4)

[[37 12]
[7 34]]

Classification report:

	precision	recall	f1-score	support
0	0.84	0.76	0.80	49
1	0.74	0.83	0.78	41
accuracy			0.79	90
macro avg	0.79	0.79	0.79	90
weighted avg	0.79	0.79	0.79	90

Random forest results (Figure 5)

Accuracy: 0.8555555555555555

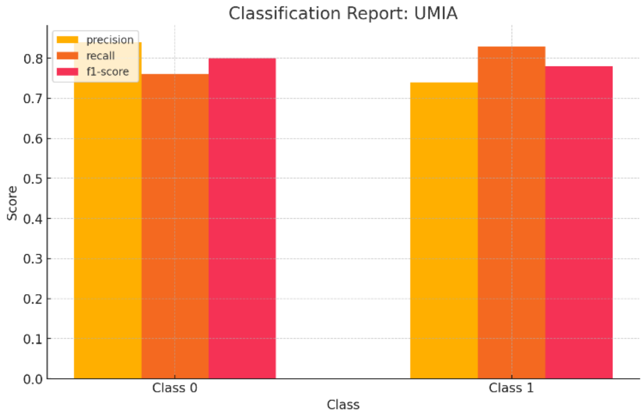

Figure 3. UMIA results

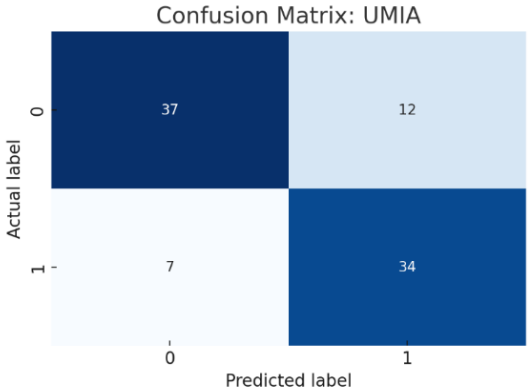

Figure 4. UMIA confusion matrix

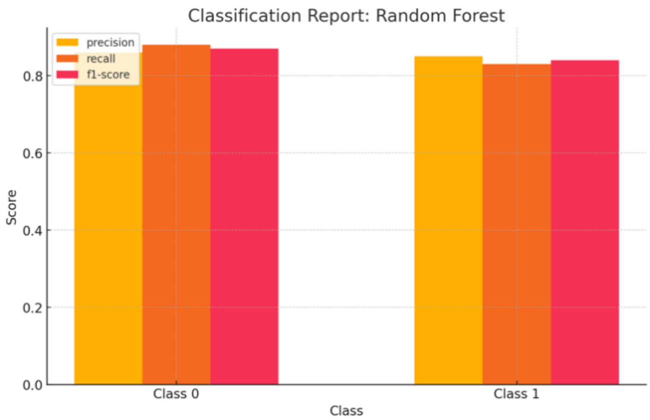

Figure 5. RF results

Confusion Matrix (Figure 6)
[[43 6]
[7 34]]
Classification report:

	precision	recall	f1-score	support
0	0.86	0.88	0.87	49
1	0.85	0.83	0.84	41
accuracy			0.79	90
macro avg	0.85	0.85	0.85	90
weighted avg	0.86	0.86	0.86	90

SVM results (Figure 7)
Accuracy: 0.6666666666666666

Confusion matrix (Figure 8)
[[44 5]
[25 16]]
Classification report:

	precision	recall	f1-score	support
0	0.64	0.90	0.75	49
1	0.76	0.39	0.52	41
accuracy			0.67	90
macro avg	0.70	0.64	0.63	90
weighted avg	0.69	0.67	0.64	90

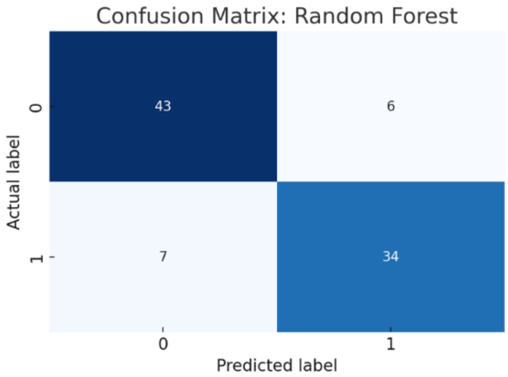

Figure 6. RF confusion matrix

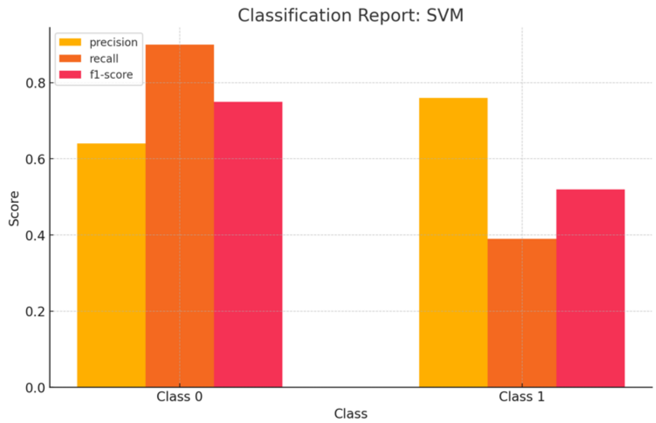

Figure 7. SVM results

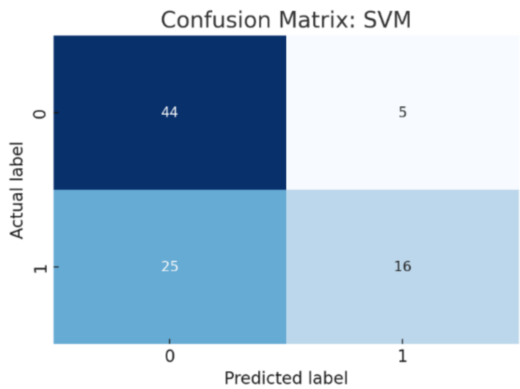

Figure 8. SVM confusion matrix

Here is a detailed comparison done for the three models UMIA, Random Forest, and SVM on the basis of accuracy, precision, recall, and F1-score. Let's comparing the performance from various aspects.

Accuracy:

•Random Forest comes with the highest accuracy at 85.56%, indicating it did the most correct predictions overall.

•UMIA performed reasonably well with its accuracy at 78.89%, decent yet lower than Random Forest.

•SVM had the lowest accuracy at 66.67%, which denotes very poor performance on the data for it.

Precision (Class 0 and Class 1):

•For Class 0-Representing a patient with no heart disease, the precision is highest for Random Forest, about 86%, while the closest result is UMIA, which has 84%. In the case of SVM, precision is as low as 64%.

•Precision for Class 1: heart disease, again, with Random Forest on top at 85%, followed by SVM at 76% and UMIA at 74%. Precision in this case tells how many of the positive predictions were actually correct. Here both UMIA and Random Forest performed well enough.

Recall (Class 0 and Class 1)

•Class 0 recall, where a patient correctly has no heart disease, is highest for SVM at 90%, then Random Forest at 88%, and then UMIA at 76%.

•Class 1 recall, where a patient correctly has heart disease, shows where SVM really falls behind at only 39%. Both UMIA and Random Forest achieve a strong 83% recall for this class.

F1-Score (Class 0 and Class 1):

•F1-Score Class 0: It gives a good balance between precision and recall; the first place is Random Forest at 87%, followed by UMIA at 80%, whereas SVM stood at 75%.

•F1-Score Class 1: Random Forest is at the top with 84%, while UMIA is in second place with 78%, whereas for SVM, it is the lowest with 52%.

General insights:

•Random Forest has been continuously established to be the best across most metrics among these models, hence being the most consistent model for this dataset.

•UMIA performs relatively well and actually produces competitive results, especially for Recall Class 1 with its performance equal to that of Random Forest.

While SVM is performing well in recall for Class 0, its recall for Class 1 significantly underperforms, leading to lower precision and F1-score performance.

A comprehensive analysis can identify a specific strengths and weaknesses of UMIA in comparison to traditional algorithms. Random Forest was identified as the most effective model and largely due to its ensemble characteristics that successfully reduce variance, noise and the risk of overfitting. In contrast the UMIA has produced a competitive result by attaining precision comparable to Random Forest and significantly exceeding SVM in recall and F1-score metrics for the classification of heart disease cases. The suboptimal performance of SVM can be attributed to difficulties in managing the complexity and the variability that are presented in the dataset. UMIA can demonstrate a notable accuracy and its distinctive cognitive based design suggests advantages in complex or dynamic environments where conventional models may struggle. UMIA also has associative memory and subliminal perception mechanisms enable effective management of ambiguous data and rendering it advantageous for applications requiring human-like intuition or adaptability.

UMIA has showed a remarkable ability but it is necessary to recognize its limitations and potential biases. The dataset size and breadth of the evaluation might have implicitly favored traditional algorithms such as Random Forest due to their proven track record on structured medical datasets. While such selection bias might lead to underestimation of the strengths of UMIA in less structured and more complex real-world environments. Interpretability the UMIA decisions that theoretically better by virtue of its psychoanalytic foundations is still partially dimmed when operationalized into a computational term. While the practitioners are not familiar with the underlying psychological principles of its design might therefore find interpretability difficult. By generalizability it might be restricted because the algorithm's validation was conducted largely on a single domain specific dataset. Future validation across diverse datasets can be on multiple application domains will be essential for a well-rounded understanding of UMIA's strengths and weaknesses. While the proposed method has compared with different machine learning algorithms as shown in Table A1 [19-22].

6. CONCLUSIONS

The algorithm known as the UMIA is a notable advancement in the field of algorithmic design, as it combines psychological insights with computational efficiency resulting in a novel approach. The algorithm under consideration represents not only a significant technological progression, but also a noteworthy interdisciplinary integration, connecting the fields of cognitive psychology and machine learning. The development and effective implementation of this technology have the potential to yield substantial advancements in the processing of algorithms, decision-making processes and adaptability to novel data. This study has the potential to facilitate the development of artificial intelligence decision-making processes that are more intuitive, efficient and human-like to representing a noteworthy achievement in the advancement of machine learning technologies.

UMIA has potential future applications and research paths are far broader than present explorations. UMIA is new cognition inspired approach that can make a strong contribution to areas involving subtle decision making and intuitive response as in affective computing where an emotional cues and subtle context can play a key role in informing computational response in a natural and seamless manner. In cognitive robotics UMIA has subliminal data processing ability and intuitive pattern recognition capability can allow robots to learn efficiently and rapidly in open and dynamic applications. And the future research could address the algorithm interpretability by create more sophisticated subliminal threshold mechanisms and conduct large-scale real-world testing on diverse datasets to determine the practical efficacy of UMIA and advance its flexibility across a range of domains.

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APPENDIX

Appendix shows comparison between current machine learning algorithms and the proposed algorithm.

Table A1. The comparison between current machine learning algorithms and the proposed algorithm

Feature/Aspect	Neural Networks (NN) And Artificial Neural Networks (ANN)	Support Vector Machine (SVM)	Convolutional Neural Network (CNN)	Recurrent Neural Network (RNN)	Unconscious Mind-Inspired Algorithm (UMIA)
primary use	general pattern recognition, classification	classification, regression	image recognition, processing	sequence analysis, NLP	enhanced decision-making, intuitive predictions
data handling	handles large datasets, can be prone to overfitting	effective in high-dimensional spaces, less prone to overfitting	efficient in handling image data	excellent for time-series data, can struggle with long sequences	designed to process vast unconscious data patterns efficiently
learning method	supervised and unsupervised learning	mostly supervised learning	supervised learning	supervised and unsupervised learning	mimics unconscious learning processes, potentially a mix of supervised, unsupervised, and reinforcement learning

processing speed	depends on network size, can be computationally intensive	relatively fast, efficient	requires high computational power	can be slow with long dependencies	optimized for rapid unconscious-like processing
interpretability	often seen as a "black box"	more interpretable than NN	low interpretability	low interpretability	designed for higher interpretability and mirroring human unconscious reasoning
adaptability	adapts through training, can require retraining	requires parameter tuning	requires extensive training	good adaptability to be sequence changes	highly adaptive similar to human cognitive adaptability
complexity handling	handles complex patterns, but may require deep networks	good with clear margin of separation	specialized in spatial hierarchy	manages sequential complexity	capable of handling multi-dimensional unconscious complexities
human-like decision making	limited	limited	limited	limited	high - incorporates elements of human unconscious decision-making
potential for innovative application	high, especially in ai and deep learning	high in specific areas	high in image-related fields	high in language processing	extremely high in areas requiring human-like intuition and adaptability