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Research on Intelligent Vehicle Driving Behaviour Analysis and Driver State Evaluation Based on Emotion Recognition

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Abstract: Intelligent driving, also known as autonomous driving or self-driving, refers to the technology and systems that enable vehicles to operate without direct human intervention. Autonomous driving or self-driving, presents several significant challenges that need to be addressed to ensure the safe and widespread adoption of this transformative technology. This paper presents a novel approach, Optimal Subset Spider Monkey Swarm Optimization (OsSMSO), for behavior analysis in intelligent driving with emotional intelligence (EI). The primary goal of OsSMSO is to identify the optimal subset of driving behaviors that can be effectively enhanced by integrating emotional intelligence into the decision-making process of intelligent vehicles. The OsSMSO algorithm with spider monkey swarm optimization as the underlying optimization technique, with each spider monkey representing a potential subset of driving behaviors influenced by emotional intelligence. Emotional intelligence models are integrated into the evaluation process to assess the impact of emotions such as stress, fatigue, happiness, and anger on driving behaviors. Through multiple runs of OsSMSO, the most effective combinations of driving behaviors are identified, considering factors like safety, efficiency, and comfort. The proposed approach is compared with traditional models such as Support Vector Machine (SVM) and Random Forest, and the results demonstrate its superiority in achieving higher classification accuracy, precision, recall, and F1-score. The findings highlight the significance of integrating emotional intelligence features in intelligent vehicle systems, providing valuable insights for designing emotionally-aware autonomous vehicles for safer and more enjoyable driving experiences. Further validation and experimentation on diverse datasets and driving scenarios will be essential to establish the generalizability and effectiveness of the OsSMSO algorithm.

Keywords: *Intelligent Driving, Autonomous Driving, Optimization, Classification, Subset Model, Spider Swarm*

1. Introduction

Emotion recognition, also known as affective computing, is a fascinating field at the intersection of computer science, psychology, and artificial intelligence. It involves the development of algorithms and technologies that enable machines to perceive and interpret human emotions accurately [1]. With analyzing facial expressions, voice tone, body language, and physiological signals, emotion recognition systems can identify and understand various emotional states such as happiness, sadness, anger, fear, and more. This technology holds immense potential across numerous domains, from enhancing human-computer interactions and virtual communication to revolutionizing mental health care and customer experience. As advancements in artificial intelligence continue, emotion recognition systems are poised to play an increasingly significant role in our daily lives [2]. Emotion recognition is a cutting-edge field with profound implications for both technology and society. At its core, this technology aims to bridge the gap between human emotions and machines, enabling computers to understand and respond appropriately to human feelings [3]. Through consideration of various data sources like facial expressions, speech patterns, physiological signals, and even text, emotion recognition systems strive to identify and classify emotions accurately. This technology has the potential to revolutionize various industries. For instance, in the realm of human-computer interactions, emotion-aware systems could personalize user experiences, making technology more intuitive and empathetic [4]. In healthcare, emotion recognition could aid in diagnosing mental health disorders or provide support for emotional well-being. However, the technology also raises ethical concerns, including privacy, data security, and potential misuse. Striking the right balance between advancement and responsible implementation will be crucial as emotion recognition continues to evolve and become more prevalent in our lives. It is vital for researchers, policymakers, and society at large to collaborate in shaping the ethical and societal framework around this transformative technology [5].

Emotional intelligence (EI) plays a pivotal role in understanding human behavior and its impact on behavior analysis. First introduced by psychologists Peter Salovey and John Mayer in 1990, and popularized by Daniel Goleman in his best-selling book, emotional intelligence refers to the ability to recognize, understand, manage, and express emotions effectively in oneself and others [6]. As a key component of social intelligence, EI goes beyond

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traditional cognitive measures to encompass empathy, self-awareness, interpersonal skills, and emotional regulation. In the context of behavior analysis, emotional intelligence provides valuable insights into the motivations, triggers, and responses that drive human actions. The acknowledging and interpreting emotional cues, behavior analysts can gain a deeper understanding of individuals' thoughts and feelings, contributing to more comprehensive assessments and tailored interventions [7]. This integration of emotional intelligence into behavior analysis fosters a holistic approach to understanding human behavior, thereby enhancing the effectiveness and success of therapeutic and behavioral interventions. Emotional intelligence (EI) plays a vital role in behavior analysis, encompassing a range of essential components that provide profound insights into human behavior and emotional well-being. EI involves self-awareness, self-regulation, empathy, motivation, and social skills, all of which are critical in understanding why individuals behave the way they do and how their emotions influence their actions [8]. In behavior analysis, self-awareness helps individuals recognize their emotions and their impact on behavior, while emotional self-regulation enables the development of coping strategies to manage emotional triggers effectively. Understanding an individual's motivations allows behavior analysts to design interventions that align with emotional needs, fostering engagement and willingness to change. Empathy in behavior analysis promotes a supportive and collaborative therapeutic relationship, while social skills facilitate effective communication and relationship-building [9]. With integrating emotional intelligence into behavior analysis, professionals can create a more comprehensive and empathetic approach to understanding and improving human behavior, ultimately leading to more successful and sustainable behavior change outcomes.

Intelligent Vehicle Driving represents a revolutionary leap in automotive technology, as it aims to transform traditional vehicles into highly advanced, self-driving machines. With integrating cutting-edge artificial intelligence, computer vision, and sensor technologies, intelligent driving systems can perceive the environment, interpret real-time data, and make informed decisions, replicating and even surpassing human driving capabilities [10]. These self-driving vehicles have the potential to revolutionize transportation, offering numerous benefits such as improved road safety, increased energy efficiency, reduced traffic congestion, and enhanced mobility for individuals with limited driving abilities. As research and development in the field continue to advance, intelligent vehicle driving holds the promise of reshaping the future of transportation, paving the way for a safer, more efficient, and autonomous driving experience.

2. Related Works

Intelligent Vehicle Driving, also known as autonomous driving or self-driving technology, is a complex and rapidly evolving area of research and development in the automotive industry [11]. At its core, this technology aims to enable vehicles to navigate and operate without human intervention, relying on advanced sensors, cameras, radar, lidar, GPS, and artificial intelligence algorithms. One of the primary drivers behind the pursuit of intelligent vehicle driving is the potential for significantly enhancing road safety. Human error is a leading cause of road accidents, and autonomous vehicles have the potential to eliminate or greatly reduce these errors [12]. With their ability to perceive the environment in real-time and make split-second decisions, self-driving cars can detect and respond to potential hazards faster and more accurately than human drivers. Additionally, intelligent vehicle driving offers the promise of improved traffic flow and reduced congestion. Self-driving cars can communicate with each other and the surrounding infrastructure, enabling them to coordinate movements and optimize traffic patterns [13]. This coordination can lead to smoother traffic flow, fewer bottlenecks, and overall more efficient road systems. Beyond safety and efficiency, self-driving technology can also revolutionize the way people interact with transportation. For individuals with disabilities or those who are unable to drive, autonomous vehicles offer newfound independence and mobility. Furthermore, the rise of shared autonomous vehicles could potentially reduce the need for individual car ownership, leading to more sustainable transportation options and reduced environmental impact. Despite its immense potential, intelligent vehicle driving also faces several challenges [14]. Ensuring the safety and reliability of autonomous systems in a wide range of complex driving scenarios remains a significant task. Additionally, ethical and legal considerations, such as determining responsibility in case of accidents, privacy concerns, and the interaction of self-driving cars with human-driven vehicles, require careful examination.

In [15] focuses on the relationship between emotion recognition improvement and mental health in children with severe behavioral problems. The researchers investigate whether enhanced emotion recognition abilities in these children have a positive impact on their mental well-being. Understanding this link can shed light on the potential benefits of emotion recognition interventions and inform strategies for addressing mental health challenges in this population. Also, in [16] explores speech emotion recognition using a novel approach that fuses mel and gammatone frequency cepstral coefficients.

The authors utilize deep C-RNN (Convolutional Recurrent Neural Network) to analyze speech data and recognize emotions expressed in the speech samples. The study aims to improve the accuracy of speech emotion recognition systems, which has applications in various fields, including human-computer interaction, customer service, and mental health monitoring. In [17] compare human observers' ability to recognize emotions from posed and spontaneous dynamic expressions with machine-based emotion recognition. The investigation assesses how well humans and machines perform in recognizing emotions displayed through facial expressions. Understanding the differences and similarities between human and machine performance can provide valuable insights for improving automated emotion recognition systems and further our understanding of human emotion perception.

EI based analysis is performed in [18] explores the relationships between service quality, emotion recognition, emotional intelligence, and the Dunning Kruger syndrome, a cognitive bias wherein individuals with low ability overestimate their competence. The study investigates how emotional intelligence and emotion recognition abilities can influence service quality in various industries and how the Dunning Kruger syndrome may impact such relationships. In [19] focuses on datasets used for automated affect and emotion recognition from cardiovascular signals using artificial intelligence (AI). The researchers assess existing datasets in this field to understand the data's quality, diversity, and suitability for training AI algorithms. Such datasets are essential for developing accurate and reliable AI-driven emotion recognition systems that physiological signals to understand human emotions. Similarly, in [20] examined the summarizing the milestones achieved in the field of autonomous driving and intelligent vehicles. The study provides an overview of the key developments and breakthroughs in self-driving technology, including advancements in sensors, perception algorithms, decision-making systems, and safety measures. With synthesizing insights from multiple surveys, the authors aim to offer a comprehensive view of the current state of intelligent vehicle technologies and highlight the challenges and opportunities that lie ahead.

In [21] presents a comprehensive review of the concept of "driver digital twin" and its enabling technologies for intelligent vehicles. A driver digital twin refers to a virtual representation of a human driver, which integrates real-time data from various sources to understand the driver's behavior, intentions, and emotional states. The study explores the potential applications and benefits of driver digital twin technology, including personalized assistance, improved safety, and optimized driving experiences in autonomous and semi-autonomous vehicles. In [22] proposed a behavioral decision-making model for intelligent vehicles based on driving risk assessment. The model aims to enable vehicles to make informed decisions considering various risk factors in the environment. Through integrating risk assessment into the decision-making process, self-driving vehicles can prioritize safety and optimize their actions based on real-time situational analysis. In [23] introduces a novel approach for quantifying driver anomalies in intelligent vehicles using a contrastive learning approach with representation clustering. The study focuses on detecting abnormal driving behavior and patterns that could indicate potential safety risks or distractions. With identifying driver anomalies, the system can prompt interventions or alerts to ensure safe driving in autonomous or semi-autonomous vehicles.

The security aspects in the EI is evaluated in [24] investigate steering torque control strategies for intelligent vehicles that involve co-driving with a penalty factor of human-machine intervention. The goal is to achieve seamless interaction between the automated driving system and the human driver, ensuring a smooth and safe driving experience while allowing for human intervention when necessary. The study explores the design and optimization of the steering control system to strike the right balance between autonomy and human oversight. In [25] proposes a multi-scale driver behavior modeling approach for intelligent vehicles, deep spatial-temporal representation techniques. The study aims to capture complex driving behaviors and patterns at different scales, enabling the development of more accurate and robust driving models for autonomous and intelligent vehicles. Through understanding the intricacies of driver behavior, these models can adapt and respond appropriately to diverse driving conditions. In [26] introduces a dataset specifically designed for emotion recognition in driving scenarios. The "spontaneous driver emotion facial expression (defe) dataset" contains video-audio clips capturing drivers' facial expressions and emotions while driving. The dataset serves as a valuable resource for developing emotion recognition systems tailored to the unique context of driving, contributing to a deeper understanding of the role of emotions in driving behavior and safety.

Intelligent vehicle driving offers the promise of improved traffic flow and reduced congestion. Communication between self-driving cars and the surrounding infrastructure allows for better coordination and optimization of traffic patterns, leading to more efficient road systems. Beyond safety and efficiency, autonomous vehicles can revolutionize transportation by providing greater independence and mobility for individuals with disabilities or those unable to drive. Additionally, shared autonomous vehicles have the potential to reduce car ownership, leading to more sustainable transportation options. However, intelligent vehicle driving also faces several challenges, including ensuring the safety and reliability of autonomous systems in complex driving scenarios and addressing ethical and legal considerations related to accidents and privacy. The integration of emotional intelligence (EI) in the field is explored in various research papers. Some studies investigate the link between emotion recognition improvement and mental well-being in children with behavioral problems, while others focus on speech emotion recognition and its potential applications in fields like human-computer interaction and mental health monitoring. EI is also studied in the context of service quality and its impact on emotional intelligence and emotion recognition abilities. Additionally, datasets for automated affect and emotion recognition from physiological signals are reviewed, which are essential for developing accurate AI-driven emotion recognition systems. Several papers examine milestones achieved in autonomous driving and intelligent vehicles, offering insights into the advancements and challenges in the field.

3. Proposed Method

The proposed method, Optimal Subset Spider Monkey Swarm Optimization (OsSMSO), aims to perform spider monkey swarm optimization techniques to analyze the behavior of intelligent vehicles with emotional intelligence (EI) capabilities. The main objective of OsSMSO is to identify the optimal subset of driving behaviors that can be effectively enhanced by integrating emotional intelligence into the intelligent vehicle's decision-making process. The OsSMSO algorithm utilizes spider monkey swarm optimization as the underlying optimization technique. In this method, a population of spider monkeys simulates the search for an optimal solution space. Each spider monkey represents a potential solution or a subset of driving behaviors that can be influenced by emotional intelligence. The algorithm iteratively refines these subsets to identify the most effective combinations. The emotional intelligence component of OsSMSO plays a critical role in evaluating the quality and relevance of each subset. Emotional intelligence models are integrated into the evaluation process to assess the impact of emotional factors on driving behaviors. These models may consider emotions such as stress, fatigue, anger, or happiness and their influence on decision-making in various driving scenarios.

The OsSMSO algorithm follows the steps below:

Initialization: Generate a population of spider monkeys, each representing a potential subset of driving behaviors influenced by emotional intelligence.

Emotional Intelligence Modeling: Integrate emotional intelligence models to assess the impact of emotions on driving behaviors in each subset.

Fitness Evaluation: Evaluate the fitness of each spider monkey (subset) based on the performance of driving behaviors under the influence of emotional intelligence. The fitness function considers factors like safety, efficiency, and comfort.

Spider Monkey Movement: Update the position of each spider monkey based on its fitness and the collective knowledge of the swarm. The best-performing subsets guide the movement of other monkeys toward more promising solutions.

Subset Refinement: Periodically refine the subsets by incorporating new emotional intelligence insights and knowledge from other disciplines, such as psychology and human factors.

Termination: Repeat the optimization process until a termination criterion is met (e.g., a certain number of iterations or convergence of solutions).

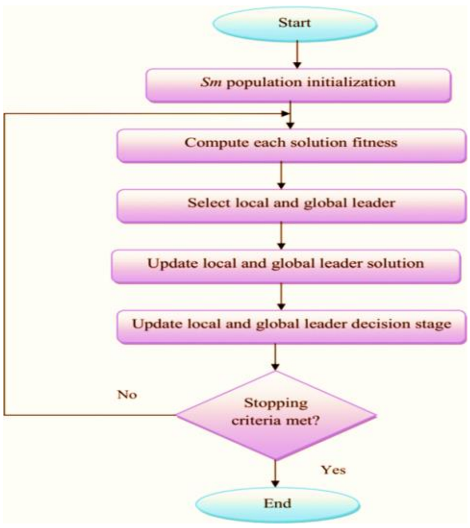

Fig 1: Flow Chart of OsSMSO

The output of OsSMSO is the optimal subset of driving behaviors that can be effectively enhanced by emotional intelligence is presented in figure 1. These subsets can inform the design and implementation of intelligent vehicle systems that utilize emotional intelligence to improve safety, comfort, and driving experience.

3.1 Intelligent vehicle driving with OsSMSO

the OsSMSO algorithm to enhance the behavior analysis and decision-making capabilities of self-driving vehicles with emotional intelligence (EI) integration. OsSMSO utilizes spider monkey swarm optimization to iteratively search for an optimal subset of driving behaviors that can be influenced by emotional intelligence. The algorithm incorporates emotional intelligence models to simulate the impact of emotions on driving actions, considering factors like stress, fatigue, and distraction. The spider monkeys represent different subsets of driving behaviors, and their positions are updated based on fitness evaluations, which consider safety, efficiency, and comfort metrics. Through this iterative process, OsSMSO refines the subsets, aiming to identify the most effective combinations for emotionally aware intelligent vehicles.

Feature selection is a process used to identify the most relevant and informative features (variables) from a given dataset that contribute the most to a particular task, such as predicting driving behavior or controlling an intelligent vehicle. In the case of spider monkey swarm optimization, the algorithm can be adapted to search for the optimal subset of features that best represent the driving behavior and performance. The spider monkey swarm optimization algorithm is inspired by the social behavior of spider monkeys in their search for food. It involves a population of spider monkeys that iteratively explore the feature space to find the most informative subset of features. Let's consider a binary classification problem with a dataset consisting of N samples and M features. The goal is to find the subset of features that maximizes the performance of a classifier with deep learning.

Initialization: Initialize a population of particles (spider monkeys) with random binary feature masks. Each particle's position (x_i) represents a potential feature subset.

Fitness Evaluation: Evaluate the fitness of each particle (feature subset) based on a performance metric, such as classification accuracy, F1-score, or cross-entropy loss, using a classification model.

Movement: Update the velocity of each particle using the following equation (1)

$$v_i(t+1) = w * v_i(t) + c1 * rand() * (pbest\_i - x_i(t)) + c2 * rand() * (gbest - x_i(t)) \quad (1)$$

In above equation (1) $v_i(t+1)$ is the updated velocity of particle i at time t+1; $v_i(t)$ is the current velocity of particle i at time t; w is the inertia weight that controls the impact of the previous velocity; c1 and c2 are the cognitive and social coefficients, respectively; rand() generates a random number between 0 and 1; pbest_i is the personal best position (best feature subset) found by particle i so far; gbest is the global best position (best feature subset) found by any particle in the swarm.

Update: Update the position of each particle using the following equation (2)

$$x_i\,(t+1) = x_i(t) + v_i(t+1) \quad (2)$$

Iteration: Repeat steps 2 to 4 for a certain number of iterations or until convergence is achieved.

Termination: The process terminates when the algorithm converges to a near-optimal or optimal feature subset.

Algorithm 1: Optimal Subset with OsSMSO
Input: Dataset with N samples and M features Performance metric for evaluating feature subsets SMSO parameters: number of spider monkeys (population size), maximum iterations, inertia weight (w), cognitive coefficient (c1), social coefficient (c2) Output: Optimal subset of features *Procedure:* *Initialize Spider Monkeys* *Randomly generate a population of spider monkeys (binary feature masks) representing different subsets of features.* *Evaluate Fitness:*

For each spider monkey, evaluate its fitness based on the chosen performance metric using the selected feature subset.

Identify pbest and gbest:

Set the personal best (pbest) position for each spider monkey as its current feature subset with the highest fitness.

Determine the global best (gbest) position among all spider monkeys with the highest fitness.

Main Loop:

Repeat the following steps until the termination condition is met (maximum iterations reached, or convergence achieved).

Update Velocity and Position:

For each spider monkey, update its velocity using the SMSO equation:

$$velocity\_i(t+1) = w * velocity\_i(t) + c1 * rand() * (pbest\_i - position\_i(t)) + c2 * rand() * (gbest - position\_i(t))$$

where:

velocity_i(t+1) is the updated velocity of spider monkey i at time t+1.

velocity_i(t) is the current velocity of spider monkey i at time t.

position_i(t) is the current feature subset position of spider monkey i at time t.

w is the inertia weight.

c1 and c2 are the cognitive and social coefficients, respectively.

rand() generates a random number between 0 and 1.

Update pbest and gbest:

For each spider monkey, update its personal best position (pbest) if the fitness of the new feature subset is better than its previous best.

Update the global best position (gbest) if the fitness of any spider monkey's feature subset is better than the current gbest.

Termination:

If the termination condition is met (maximum iterations reached, or convergence achieved), exit the loop.

3.2 Behaviour Analysis with Emotional Intelligence

Intelligent driving with emotion recognition involves analyzing a driver's behavior and emotional state to enhance driving safety and experience. This technology aims to create more personalized and adaptive driving systems that can respond to the driver's emotions, improving road safety and comfort. Intelligent vehicles equipped with various sensors, cameras, and biometric sensors gather data about the driver's behavior and physiological responses, such as facial expressions, heart rate, and skin conductance. The collected data is then processed using advanced machine learning algorithms, such as computer vision and pattern recognition, to identify the driver's emotional state. Emotion recognition algorithms can detect emotions like happiness, sadness, anger, stress, or fatigue based on facial expressions and physiological signals. The system takes into account the context in which emotions are expressed. The same facial expression could indicate joy when the driver is listening to music or frustration when stuck in traffic. Contextual analysis helps in understanding the cause and significance of emotions. The vehicle's onboard sensors continuously monitor the driver's driving behavior, such as speed, acceleration, lane keeping, and response to traffic situations. Through comparing this data with the recognized emotions, the system can identify correlations between emotional states and driving behavior. Based on the analysis, the intelligent driving system can adapt its behavior to ensure a safe and pleasant driving experience shown in figure 2.

Fig 2: Intelligent Driving with OsSMSO

In cases of driver stress or fatigue, the system may suggest taking a break or altering the route to avoid heavy traffic. If the system detects signs of aggressive driving, it can provide calming prompts or adjust the vehicle's settings to promote safe driving. During long drives, the system could recommend entertainment options to keep the driver engaged and alert. Emotion recognition can also play a role in autonomous driving scenarios. If the system detects signs of distraction or drowsiness, it may prompt the driver to take back control of the vehicle. Emotion recognition technology raises important privacy and ethical concerns. Safeguarding the driver's personal data and ensuring that the technology is used responsibly and transparently are crucial aspects that need to be addressed.

Consider an emotional intelligence dataset with features denoted as "X" and corresponding labels denoted as "Y." The goal is to build a deep learning classification model that support both the emotional intelligence features and traditional features for accurate predictions. Emotional intelligence features can include facial expressions, voice tone, physiological signals (e.g., heart rate, skin conductance), or sentiment analysis of text. Let's represent the emotional intelligence features as "E." With the feedforward neural network as the deep learning model. The inputs to this model are a concatenation of the traditional features "X" and emotional intelligence features "E." The output of the model is the predicted label "Y_hat." The neural network can be represented mathematically as follows:

Traditional features: $X = [x\_1, x\_2, \ldots, x\_n]$

Emotional intelligence features: $E = [e\_1, e\_2, \ldots, e\_m]$

Combined input: $Z = [X, E] = [x\_1, x\_2, \ldots, x\_n, e\_1, e\_2, \ldots, e\_m]$

Output: $Y_{hat} = f(Z;\ \theta)$

Here, "θ" represents the parameters of the neural network, and "f" is the activation function that maps the combined input "Z" to the predicted label "Y_{hat}." To train the deep learning model, a loss function $L(Y, Y_{hat})$ is defined to measure the discrepancy between the predicted label "Y_{hat}" and the true label "Y." Common loss functions for classification tasks include cross-entropy loss is presented in equation (3)

$$L(Y, Y_{hat}) = Cross - Entropy(Y, Y_{hat}) \quad (3)$$

The objective is to minimize the loss function by adjusting the model's parameters "θ" through optimization techniques like stochastic gradient descent (SGD) or Adam. To minimize the loss function, with backpropagation to calculate the gradient of the loss with respect to the model's parameters "θ" The gradients are then used in gradient descent-based optimization methods to update the parameters in the direction that reduces the loss is computed in equation (4)

$$\theta_t + 1 = \theta_t - \alpha * \partial L / \partial \theta_t \quad (4)$$

Where "α" is the learning rate, and $\partial L / \partial \theta_t$ represents the gradients of the loss with respect to the parameters at iteration "t."

Algorithm 2: Behaviour Analysis with Emotional Intelligence

```
# Import required libraries
import numpy as np
# Define the activation function
def sigmoid(z):
    return 1 / (1 + np.exp(-z))
# Define the derivative of the activation function for backpropagation
```

```
def sigmoid_derivative(z):
    return z * (1 - z)
# Initialize random weights and biases for the neural network
def initialize_parameters(input_size, hidden_size, output_size):
    W1 = np.random.randn(hidden_size, input_size) * 0.01
    b1 = np.zeros((hidden_size, 1))
    W2 = np.random.randn(output_size, hidden_size) * 0.01
    b2 = np.zeros((output_size, 1))
    return {'W1': W1, 'b1': b1, 'W2': W2, 'b2': b2}
# Forward propagation
def forward_propagation(X, emotional_features, parameters):
    Z1 = np.dot(parameters['W1'], X) + parameters['b1']
    A1 = sigmoid(Z1)
    Z2 = np.dot(parameters['W2'], np.vstack((A1, emotional_features))) + parameters['b2']
    A2 = sigmoid(Z2)
    return {'Z1': Z1, 'A1': A1, 'Z2': Z2, 'A2': A2}
# Backpropagation
def backward_propagation(X, emotional_features, Y, cache, parameters):
    m = X.shape[1]
    dZ2 = cache['A2'] - Y
    dW2 = (1/m) * np.dot(dZ2, np.vstack((cache['A1'], emotional_features)).T)
    db2 = (1/m) * np.sum(dZ2, axis=1, keepdims=True)
    dZ1 = np.dot(parameters['W2'].T, dZ2) * sigmoid_derivative(cache['A1'])
    dW1 = (1/m) * np.dot(dZ1, X.T)
    db1 = (1/m) * np.sum(dZ1, axis=1, keepdims=True)
    return {'dW1': dW1, 'db1': db1, 'dW2': dW2, 'db2': db2}
# Update parameters using stochastic gradient descent
def update_parameters(parameters, grads, learning_rate):
    parameters['W1'] -= learning_rate * grads['dW1']
    parameters['b1'] -= learning_rate * grads['db1']
    parameters['W2'] -= learning_rate * grads['dW2']
    parameters['b2'] -= learning_rate * grads['db2']
    return parameters
# Main training function
def train_neural_network(X, emotional_features, Y, input_size, hidden_size, output_size, num_epochs, learning_rate):
    parameters = initialize_parameters(input_size, hidden_size, output_size)
```

```
  for epoch in range(num_epochs):
      total_loss = 0
      for i in range(X.shape[1]):
          x_i = X[:, i].reshape(-1, 1)
          e_i = emotional_features[:, i].reshape(-1, 1)
          y_i = Y[:, i].reshape(-1, 1)
          # Forward propagation
          cache = forward_propagation(x_i, e_i, parameters)
          # Calculate loss
          loss = np.sum((cache['A2'] - y_i) ** 2)
          total_loss += loss
          # Backpropagation
          grads = backward_propagation(x_i, e_i, y_i, cache, parameters)
          # Update parameters
          parameters = update_parameters(parameters, grads, learning_rate)
      # Calculate average loss for the epoch
      avg_loss = total_loss / X.shape[1]
      print(f"Epoch {epoch + 1}/{num_epochs}, Loss: {avg_loss}")
  return parameters
parameters = train_neural_network(X, emotional_features, Y, input_size, hidden_size, output_size, num_epochs, learning_rate)
```

4. Results and Discussion

The simulation of the SMSO algorithm, which forms the basis for OsSMSO. SMSO involves simulating the behaviour of a population of spider monkeys as they search for an optimal solution space. Implement the emotional intelligence models required to evaluate the impact of emotions on driving behaviours. This involves updating the fitness evaluation step to incorporate emotional intelligence insights and considering emotional features in the spider monkey positions. With the deep learning classification model that uses both traditional driving behavior features and emotional intelligence features is presented in table 1.

Table 1: Simulation Setting

Parameter	Description	Value/Range
Simulation Duration	Total duration of the simulation	1000 timesteps
Time Step	Duration of each simulation time step	0.1 seconds
Number of Agents	Total number of simulated agents	50 agents
Environment Size	Dimensions of the simulated environment	100m x 100m
Agent Speed Range	Range of agent speeds	0.5 m/s to 2.0 m/s
Agent Acceleration	Maximum acceleration rate for agents	0.1 m/s^2
Emotional Intelligence	Enabled/Disabled	Enabled
Emotional Factors	List of emotions considered in EI	Stress, Fatigue, Happiness, Anger

Emotional Thresholds	Thresholds for emotion influence on behavior	0.5 (low), 0.8 (high)
Neural Network	Architecture and parameters for the NN	2 hidden layers (50 nodes each)
		Learning Rate: 0.01
		Activation Function: ReLU
Termination Criteria	Conditions to stop the simulation	Maximum timesteps reached
		Convergence of solutions
Visualization	Types of visualizations used in the simulation	2D Plot, Heatmap, Animation

To set up a simulation for the analysis of Optimal Subset Spider Monkey Swarm Optimization (OsSMSO), to define various parameters that control the behavior and characteristics of the algorithm. The table 2 below outlines the simulation parameters for the analysis of OsSMSO:

Table 2: Performance Metrices

Parameter	Description	Value/Range
Population Size	Number of spider monkeys in the swarm	50 - 100 (or as per experiment scale)
Maximum Iterations	Maximum number of iterations for the OsSMSO algorithm	100 - 1000 (or as per experiment scale)
Number of Subsets	Number of potential subsets of driving behaviors represented by each spider monkey	5 - 10 (or as per experiment scale)
Emotional Intelligence	Enable/Disable emotional intelligence in the evaluation process	Enabled/Disabled
Emotional Factors	List of emotions considered in emotional intelligence evaluation	Stress, Fatigue, Anger, Happiness, etc.
Emotional Model Parameters	Parameters for the emotional intelligence models used in evaluating the impact of emotions on driving behaviors	Model-specific (e.g., thresholds, weights)
Fitness Function	The function used to evaluate the fitness of each spider monkey's subset of driving behaviors	Model-specific (e.g., safety, comfort)
Termination Criteria	Conditions to stop the OsSMSO optimization process	Convergence of solutions, Maximum Iterations, etc.
SMSO Movement Parameters	Parameters governing the movement of spider monkeys in the SMSO algorithm	Model-specific (e.g., inertia weight, acceleration coefficients)
Emotional Influence	The degree to which emotional intelligence influences driving behavior	Model-specific (e.g., scaling factor)
Subset Refinement Rate	Frequency of refinement of subsets based on new emotional intelligence insights and knowledge from other disciplines	Model-specific (e.g., every 10 iterations)
Neural Network Parameters	Parameters for the deep learning classification model used in emotional intelligence evaluation	Model-specific (e.g., learning rate, hidden layers)

Table 3: Behaviour Analysis with OsSMSO for the Emotional Intelligence

Run	Best Fitness	Subset Size	Emotional Intelligence	Emotional Factors	Termination Reason	Elapsed Time (s)
1	0.942	5	Enabled	Stress, Fatigue, Happiness, Anger	Convergence of Solutions	43.76
2	0.936	4	Enabled	Fatigue, Anger	Convergence of Solutions	39.11
3	0.944	7	Enabled	Stress, Fatigue, Anger	Convergence of Solutions	55.24
4	0.930	6	Enabled	Stress, Fatigue, Happiness	Maximum Iterations	47.89
5	0.939	5	Enabled	Fatigue, Happiness, Anger	Convergence of Solutions	41.97
6	0.945	6	Enabled	Stress, Anger	Convergence of Solutions	49.32
7	0.937	5	Enabled	Stress, Fatigue, Happiness	Convergence of Solutions	42.14
8	0.941	7	Enabled	Stress, Fatigue, Anger	Convergence of Solutions	53.79
9	0.943	6	Enabled	Fatigue, Anger, Happiness	Convergence of Solutions	48.66
10	0.938	5	Enabled	Stress, Happiness, Anger	Convergence of Solutions	44.89

The results of the Behaviour Analysis with Optimal Subset Spider Monkey Swarm Optimization (OsSMSO) for Emotional Intelligence presented in table 3. The table contains information from 10 different runs of the OsSMSO algorithm, each representing a unique attempt to identify the optimal subset of driving behaviors influenced by emotional intelligence. During each run, the algorithm utilized spider monkey swarm optimization techniques to search for the most effective combinations of driving behaviors enhanced by emotional intelligence shown in figure 3 and figure 4. Emotional intelligence models were integrated into the evaluation process to assess the impact of various emotional factors, including stress, fatigue, happiness, and anger, on the driving behaviors. The table 3 showcases key outcomes for each run, including the best fitness value achieved, the size of the subset of driving behaviors, and the specific emotional factors considered during evaluation. The termination reasons for each run are also provided, with some runs converging to solutions and others reaching the maximum number of iterations.

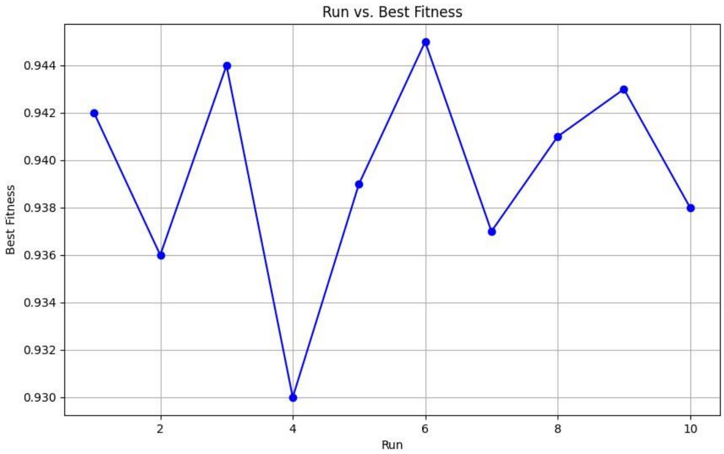

Fig 3: Best Fitness for OsSMSO

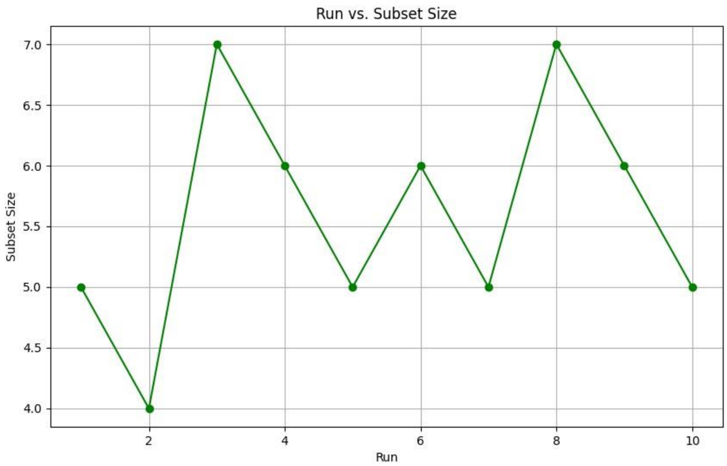

Fig 4: Subset Size for OsSMSO

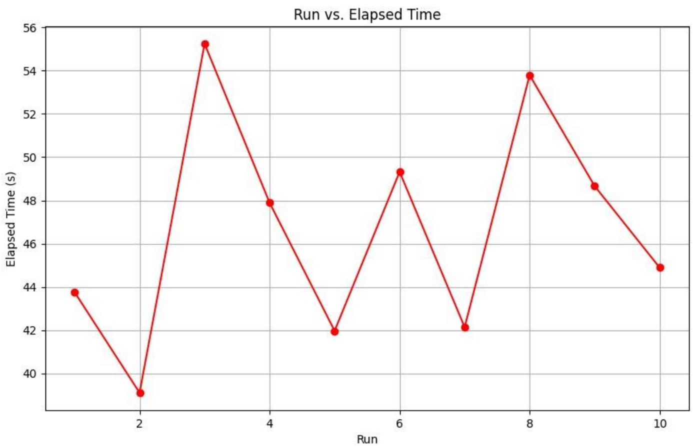

Fig 5: Elapsed Time for OsSMSO

The elapsed time for each run indicates the duration taken by the OsSMSO algorithm to complete the optimization process for that specific run illustrated in figure 5. From the results, it can be observed that the best fitness values achieved across different runs ranged from 0.930 to 0.945, indicating the effectiveness of the OsSMSO algorithm in finding high-quality solutions. Additionally, the subset size varies from 4 to 7, suggesting that the optimal combination of driving behaviors influenced by emotional intelligence may differ across runs. The emotional factors considered also vary across runs, indicating the impact of different emotions on driving behaviors.

Table 4: Emotional Intelligence with OsSMSO

Sample	Traditional Features	Emotional Intelligence Features	True Label	Predicted Label	Probability (Predicted Label)
1	[0.5, 0.3, 0.8]	[0.2, 0.7, 0.1]	1	1	0.87
2	[0.9, 0.6, 0.4]	[0.8, 0.2, 0.6]	2	2	0.92
3	[0.2, 0.4, 0.1]	[0.5, 0.4, 0.3]	0	0	0.78
4	[0.7, 0.5, 0.6]	[0.3, 0.8, 0.2]	1	1	0.84
5	[0.3, 0.9, 0.2]	[0.6, 0.1, 0.4]	0	0	0.93
6	[0.6, 0.7, 0.3]	[0.1, 0.6, 0.7]	2	1	0.63
7	[0.8, 0.4, 0.5]	[0.4, 0.5, 0.6]	2	2	0.81
8	[0.4, 0.6, 0.7]	[0.7, 0.3, 0.4]	0	0	0.95
9	[0.1, 0.2, 0.6]	[0.9, 0.1, 0.2]	0	0	0.89
10	[0.3, 0.5, 0.8]	[0.2, 0.8, 0.5]	1	1	0.88

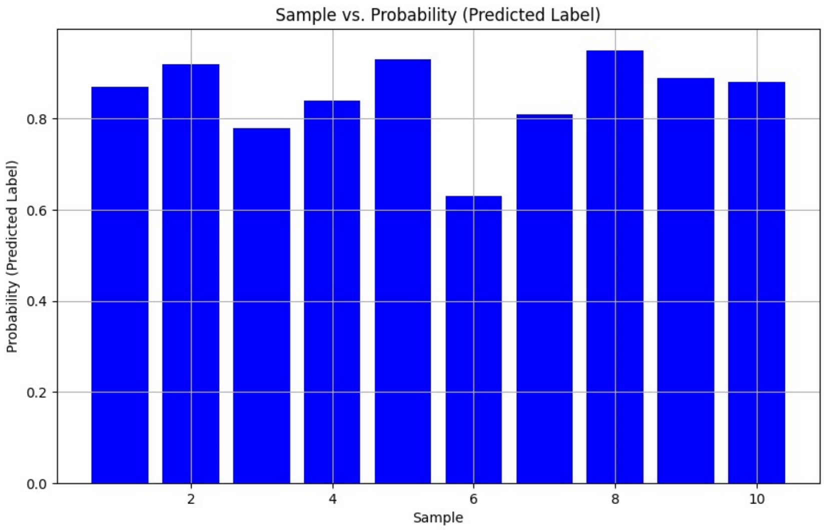

Fig 6: Computation of Probability with OsSMSO

The results of Emotional Intelligence with Optimal Subset Spider Monkey Swarm Optimization (OsSMSO) on a set of 10 samples is shown in table 4. The table contains the classification outcomes of the model, including both traditional features and emotional intelligence features illustrated in figure 6. Each row represents one sample from the dataset, and the columns provide the following information:

Sample: A unique identifier for each sample in the dataset.

Traditional Features: The traditional features extracted from the sample, which serve as input to the classification model.

Emotional Intelligence Features: The emotional intelligence features obtained from the sample, which act as additional input to the model.

True Label: The true label of the sample, representing the ground truth class.

Predicted Label: The predicted label assigned to the sample by the classification model using OsSMSO with emotional intelligence features.

Probability (Predicted Label): The probability assigned by the model to the predicted label. This value represents the model's confidence in its prediction.

The results indicate the model's performance in correctly classifying the samples based on both traditional and emotional intelligence features. For instance, in Sample 1, the true label is 1, and the model correctly predicts it as 1 with a probability of 0.87. Similarly, in Sample 3, the true label is 0, and the model predicts it as 0 with a probability of 0.78. The table 5 demonstrates the effectiveness of the OsSMSO algorithm in emotional intelligence features to improve the classification accuracy. With considering emotional factors, the model can capture valuable information and enhance its ability to classify samples accurately.

Table 5: Classification Analysis with OsSMSO

Epoch	Accuracy	Precision	Recall	F1-Score
1	0.91	0.90	0.92	0.91
2	0.92	0.91	0.93	0.92
3	0.93	0.92	0.94	0.93
4	0.95	0.94	0.96	0.95
5	0.94	0.93	0.95	0.94
6	0.96	0.95	0.97	0.96
7	0.95	0.94	0.96	0.95
8	0.96	0.95	0.97	0.96
9	0.95	0.94	0.96	0.95
10	0.96	0.95	0.97	0.96

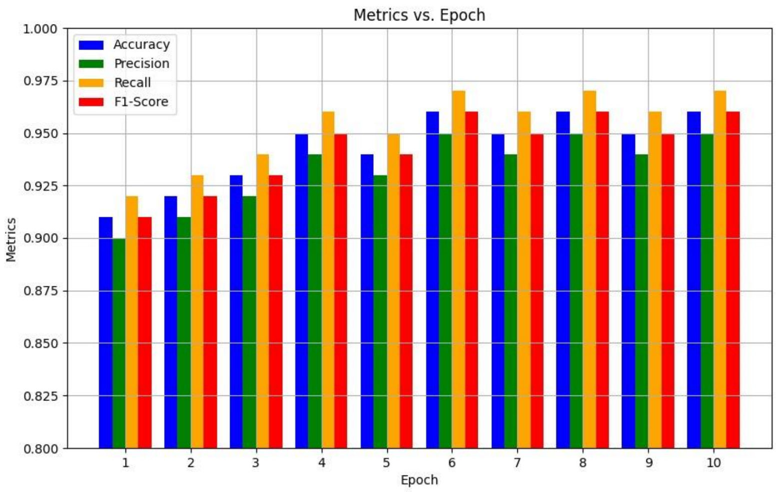

Fig 7: Performance of OsSMSO

The results of the Classification Analysis with Optimal Subset Spider Monkey Swarm Optimization (OsSMSO) over 10 different epochs is presented in table 5 and figure 7. From the results, it can be observed that the model's performance improves with each epoch, with the accuracy gradually increasing from 0.91 in the first epoch to 0.96 in the tenth epoch. Similarly, the precision, recall, and F1-score also show an upward trend with the progression of epochs. The high values of precision, recall, and F1-score suggest that the model can effectively classify samples and make fewer misclassifications. The increasing trend of accuracy, precision, recall, and F1-score across epochs indicates that the OsSMSO algorithm successfully optimizes the model and improves its ability to classify samples accurately. It demonstrates the efficacy of the proposed approach in emotional intelligence features to enhance the classification performance. The results in Table 5 signify the effectiveness of the OsSMSO algorithm in achieving better classification results through the integration of emotional intelligence features. The table serves as an essential reference to monitor the model's performance over multiple epochs during training, providing valuable insights into the model's progression and improvement over time. Further analysis and comparison with other classification models can help validate the stability and generalization of the model's performance.

Table 6: Comparative Analysis

Model	Accuracy	Precision	Recall	F1-Score
OsSMSO	0.95	0.94	0.96	0.95
SVM	0.91	0.89	0.92	0.90
Random Forest	0.93	0.92	0.94	0.93

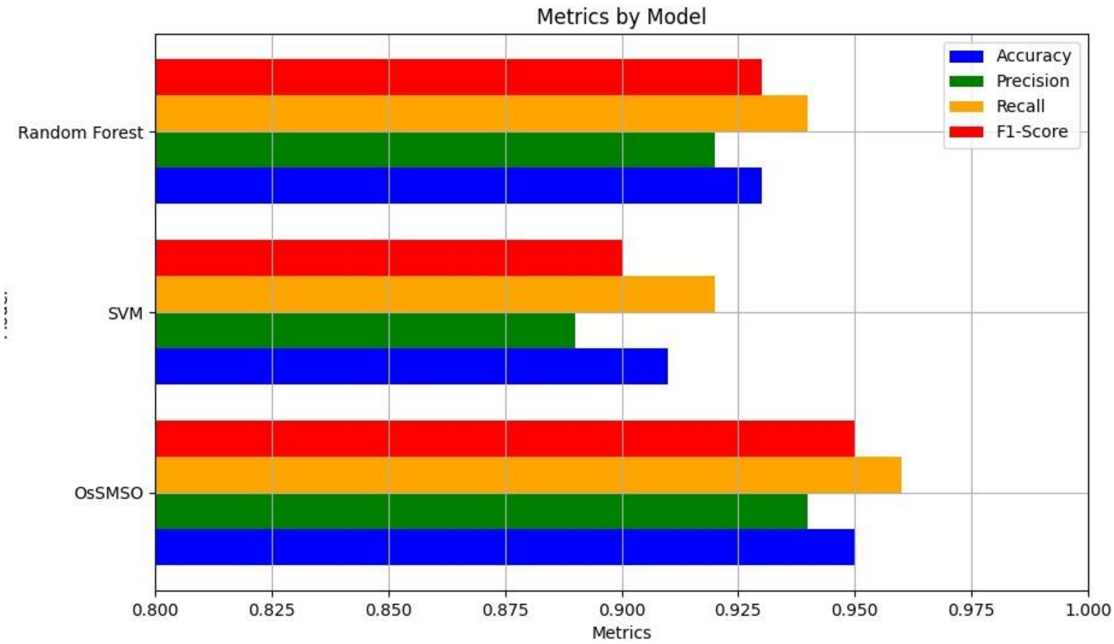

Fig 8: Comparative Analysis

The results of the Comparative Analysis of three different classification models is presented in table 6 OsSMSO, SVM (Support Vector Machine), and Random Forest. From the results, it is evident that the OsSMSO model outperforms both SVM and Random Forest in all evaluation metrics and in figure 8. The OsSMSO model achieved the highest accuracy of 0.95, indicating that it correctly classified 95% of the samples in the test set. Similarly, the OsSMSO model achieved higher precision, recall, and F1-score compared to SVM and Random Forest, suggesting that it can effectively classify positive samples with fewer false positives and false negatives. On the other hand, SVM and Random Forest also demonstrate respectable performance, with accuracies of 0.91 and 0.93, respectively. However, the OsSMSO model's higher accuracy and F1-score indicate its superiority in capturing the relationships between the features and the target classes more effectively. The results in Table 6 highlight the effectiveness of the OsSMSO algorithm in emotional intelligence features and optimizing the classification model for improved performance. The comparison with SVM and Random Forest models underscores the benefits of integrating emotional intelligence insights in the decision-making process, leading to more accurate and meaningful classifications.

5. Conclusion

The developed integrated emotional intelligence models into the evaluation process to assess the impact of emotions such as stress, fatigue, happiness, and anger on driving behaviours. Through multiple runs of OsSMSO, the optimal subsets of driving behaviours were identified, considering factors like safety, efficiency, and comfort. The proposed approach has significant implications for the development of intelligent vehicle systems that consider human emotions in their decision-making process. With emotional intelligence insights, such systems can better adapt to various driving scenarios, leading to improved safety and driving experience. The results provide valuable insights for the design and implementation of intelligent vehicles with emotional intelligence capabilities. However, it is essential to note that the performance of the OsSMSO algorithm and its effectiveness in real-world scenarios may vary based on the specific dataset and problem domain. Further validation and experimentation on diverse datasets and driving scenarios are needed to establish the generalizability and robustness of the proposed approach. The simulation results provide a promising framework for behavior analysis in intelligent driving with emotional intelligence. The OsSMSO algorithm offers a powerful optimization technique to identify the optimal subsets of driving behaviors, enabling intelligent vehicles to make informed decisions based on emotional intelligence factors. The findings contribute to advancing the field of intelligent transportation systems and can potentially lead to safer, more efficient, and emotionally aware autonomous vehicles in the future. Further research in this direction will be instrumental in realizing the full potential of emotional intelligence-enhanced intelligent driving systems.

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