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Rural Landscape Pattern Analysis and Optimization Model Construction Based on Remote Sensing Technology

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Abstract: Rural landscape pattern analysis involves the examination of the spatial arrangement and composition of land cover types in rural areas. in rural landscape pattern analysis encompass challenges such as data availability, scale discrepancies, and methodological complexities. Limited access to high-resolution spatial data, particularly in remote or developing regions, can impede accurate analysis and interpretation. Scale discrepancies between the spatial extent of data sources and the ecological processes being studied can also affect the reliability of findings. Hence, this paper proposes Genetic Optimized Stimulated Annealing Multi-Spectral (GSA-MS) for the pattern analysis. The proposed GSA-MS model uses multi-spectral features for the analysis of the images and processing. With the GSA-MS model features are extracted in the rural images for the estimation of patterns. With the GSA-MS model the features in the multi-spectral images are estimated and classified. The estimated features are optimized with the stimulated annealing model for the estimation and classification of patterns in rural images. Based on the computed and estimated features the LSTM-based deep learning model is implemented for the pattern classification in the rural area. By utilizing multi-spectral data, the model captures a broader range of information, enabling a more comprehensive analysis of rural landscapes. Specifically, the GSA-MS model optimizes the extracted features using a simulated annealing algorithm, which iteratively refines the feature set to improve pattern estimation and classification accuracy in rural images. Additionally, the paper proposes the integration of a Long Short-Term Memory (LSTM) based deep learning model for further enhancing pattern classification accuracy in rural areas. Simulation results demonstrated that the proposed GSA-MS model achieves a higher classification accuracy of 99% for the estimation of patterns in the images with a minimal loss of 0.09.

Keywords: *Rural Area, Deep Learning, Classification, Optimization, Pattern, Multi-Spectral Images*

1. Introduction

Remote sensing technology plays a pivotal role in various fields, including environmental monitoring, natural resource management, urban planning, agriculture, and disaster response [1]. This technology involves the acquisition of information about objects or phenomena on Earth's surface without direct physical contact, typically utilizing sensors mounted on satellites, aircraft, drones, or ground-based platforms. Remote sensing systems capture data across different parts of the electromagnetic spectrum, ranging from visible light to microwaves, allowing for the detection of diverse features and processes [2]. Satellite remote sensing is particularly valuable for its wide spatial coverage, frequent revisits, and long-term data archives, enabling comprehensive monitoring of large-scale environmental changes over time. These changes can include deforestation, urban expansion, land degradation, and sea-level rise, among others [3]. By analyzing satellite imagery and derived products, such as vegetation indices, land surface temperature maps, and land cover classifications, researchers can assess ecosystem health, monitor land use dynamics, and detect environmental hazards or anomalies. Furthermore, remote sensing technology facilitates the mapping and characterization of natural resources, including forests, wetlands, water bodies, and agricultural lands [4]. High-resolution satellite imagery and advanced image processing techniques allow for detailed assessments of vegetation structure, soil properties, and water quality, supporting sustainable land management practices and resource conservation efforts. In addition to its applications in environmental science and natural resource management, remote sensing technology also plays a crucial role in disaster management and emergency response [5]. Satellite imagery can provide rapid and accurate assessments of disaster impacts, such as floods, wildfires, earthquakes, and hurricanes, enabling timely decision-making and allocation of resources for relief efforts [6]. Remote sensing technology continues to evolve, driven by advances in sensor technology, data processing algorithms, and computational capabilities. Its widespread applications offer invaluable insights into Earth's processes and dynamics, supporting informed decision-making for a wide range of societal and environmental challenges [7].

Pattern analysis involves the systematic examination of data, text, or any other information to identify recurring structures, trends, or regularities. This process aims to uncover underlying patterns that may not be immediately apparent, enabling deeper understanding and potentially predicting future occurrences [8]. In various fields such as

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data science, linguistics, psychology, and biology, pattern analysis plays a crucial role in extracting meaningful insights from complex datasets. Techniques used in pattern analysis range from simple visual inspection to advanced statistical methods and machine learning algorithms. By discerning patterns, researchers and analysts can make informed decisions [9], develop hypotheses, and derive actionable conclusions to address various challenges and improve outcomes. Pattern analysis in the context of rural landscapes involves the systematic examination of spatial arrangements and distributions of various elements within these environments [10]. This analysis aims to uncover recurring structures, relationships, and trends that characterize the landscape. Patterns can manifest in diverse forms, including the distribution of land use types, vegetation cover, settlement patterns, and infrastructure networks [11]. By applying spatial analysis techniques such as remote sensing, geographic information systems (GIS), and statistical methods, researchers can identify and interpret these patterns. Understanding patterns in rural landscapes is crucial for informing land management decisions, conservation strategies, and sustainable development initiatives [12]. It allows stakeholders to comprehend the dynamics of land use change, ecological processes, and human-environment interactions, thereby facilitating effective planning and resource allocation in rural areas. Moreover, pattern analysis serves as a foundation for assessing landscape resilience, predicting future changes, and designing interventions to mitigate potential risks and enhance the overall quality of rural environments [13].

Rural landscape pattern analysis and optimization model construction based on remote sensing technology is a multidisciplinary approach that integrates spatial analysis techniques, remote sensing data, and computational modeling to understand and improve the structure and function of rural landscapes [14]. This methodology involves the systematic examination of land cover, land use, and spatial arrangements within rural areas using satellite imagery and other remote sensing data sources. By applying advanced analytical methods, such as object-based image analysis and machine learning algorithms, researchers can extract valuable information about landscape patterns, including fragmentation, connectivity, and distribution of landscape elements [15]. The construction of optimization models involves the development of computational frameworks that leverage the insights gained from pattern analysis to inform land management decisions and landscape planning strategies [16]. These models utilize mathematical algorithms and optimization techniques to identify optimal land use configurations, conservation priorities, and ecosystem service provision across rural landscapes [17]. By integrating ecological, social, and economic considerations, these models can help stakeholders balance competing interests and achieve sustainable land management outcomes. The rural landscape pattern analysis and optimization model construction based on remote sensing technology provide valuable tools for assessing landscape dynamics, identifying environmental vulnerabilities, and designing effective land management interventions [18]. By integrating cutting-edge technologies and interdisciplinary approaches, this methodology contributes to the conservation and sustainable development of rural landscapes, ensuring their long-term ecological resilience and socio-economic viability.

The paper significantly contributes to the field of rural landscape analysis by introducing a novel approach, the Genetic Optimized Stimulated Annealing Multi-Spectral (GSA-MS) model. This model represents a methodological innovation by combining genetic optimization and simulated annealing techniques with multi-spectral feature extraction, providing a robust framework for accurately estimating and classifying patterns in rural landscapes. Through comprehensive feature extraction and optimization processes, the GSA-MS model consistently achieves high classification accuracy, exceeding 96% across multiple samples. Additionally, the integration of a Long Short-Term Memory (LSTM) based deep learning model further enhances classification accuracy, allowing for the identification of complex patterns within rural landscapes. Comparative analysis with traditional classifiers such as Support Vector Machine (SVM) and Random Forest demonstrates the superior performance of the GSA-MS model in terms of accuracy, sensitivity, and specificity. These findings have practical implications for land managers, environmental policymakers, and researchers, offering valuable insights for sustainable land use practices and ecosystem conservation efforts.

2. Related Works

In the field of remote sensing technology encompass a broad spectrum of research endeavors aimed at advancing methodologies, applications, and understanding across various disciplines. Within environmental science, studies often focus on the use of remote sensing data to monitor and assess changes in land cover, land use, and ecosystem dynamics. This includes research on deforestation rates in tropical rainforests, urban expansion patterns, agricultural land management practices, and biodiversity conservation efforts. Additionally, remote sensing plays a crucial role in climate change research by providing data for monitoring key indicators such as sea surface temperature, ice cover extent, and greenhouse gas emissions. In the realm of natural resource management, related works often explore the use of satellite imagery and geospatial analysis techniques to map and characterize forests, wetlands, water bodies, and other critical habitats. These studies contribute to sustainable land use planning, resource conservation strategies, and the management of protected areas. Moreover, remote sensing technology is increasingly applied in disaster management and emergency response, with research focusing on the development of rapid assessment tools, early warning systems, and damage mapping methodologies for various natural hazards such as floods, wildfires, earthquakes, and hurricanes. Overall, related works in remote sensing encompass a diverse range of topics and applications, reflecting the interdisciplinary nature and wide-ranging impact of this field on science, society, and the environment.

Fan et al. (2022) contribute to the understanding and management of ecological security patterns in Liyang, China. Their work involves the construction and optimization of these patterns, which are vital for sustaining biodiversity, ecosystem functions, and human well-being. By utilizing remote sensing technology, they assess the current state of ecological security in the region and develop strategies to enhance it. This research is essential for guiding land use planning, conservation efforts, and sustainable development initiatives in Liyang, ultimately ensuring the long-term health and resilience of its ecosystems. Yang et al. (2022) focus on rural landscape planning and design, leveraging spatio-temporal big data to inform decision-making processes. Their work demonstrates the importance of integrating data-driven approaches into landscape management practices, enabling more effective and informed planning strategies. By harnessing the power of remote sensing technology, they offer insights into the dynamic interactions between human activities and the environment, facilitating the creation of resilient and sustainable rural landscapes. Qian et al. (2022) contribute to the field of ecological risk assessment by developing models that simulate the impacts of land use and landscape patterns on ecosystem services. Their research highlights the complex relationships between human activities, landscape dynamics, and ecosystem functions, emphasizing the need for integrated management approaches to mitigate environmental risks. By incorporating remote sensing data into their models, they provide valuable tools for policymakers and land managers to make informed decisions that promote both ecological health and human well-being.

Qiu et al. (2022) conducted a study on the landscape space of typical mining areas in Xuzhou city, China, from 2000 to 2020. They explored optimization strategies for carbon sink enhancement, aiming to mitigate the environmental impacts of mining activities. Zhu et al. (2023) focused on the evaluation, simulation, and optimization of land use spatial patterns for high-quality development in Zhengzhou city, China. This study contributes to sustainable urban planning efforts by assessing land use dynamics and proposing optimization strategies. Mahato and Pal (2022) conducted research on land surface thermal alteration and pattern simulation in rural landscapes, based on influencing factors. Their study contributes to understanding the dynamics of rural landscapes and their response to various environmental factors. Dong et al. (2022) investigated the construction of ecological and recreation patterns in the rural landscape space of the Dujiangyan Irrigation District in Chengdu, China. This study explores ways to integrate ecological conservation with recreational activities in rural areas. Yu et al. (2022) focused on the construction of regional ecological security patterns based on multi-criteria decision making and circuit theory. Their study aims to enhance ecological security by identifying key areas for conservation and restoration efforts.

Zhu and Cheng (2022) present a study on rural landscape design update and optimization based on a scientific computing algorithm of color template space projection. This research focuses on improving rural landscape design methodologies through advanced computational techniques. Bao et al. (2022) conducted a remote sensing-based assessment of ecosystem health using an optimized vigor-organization-resilience model. Their study provides insights into ecosystem dynamics and resilience, with a case study conducted in Fuzhou City, China. Wang et al. (2022) explore spatial and temporal variation, simulation, and prediction of land use in the ecological conservation area of Western Beijing. This study contributes to understanding land use dynamics and informing conservation efforts in ecologically sensitive areas. Wang (2022) focuses on the analysis and optimization of tourism landscape patterns based on GIS (Geographic Information Systems). This research aims to enhance tourism planning and management through the application of spatial analysis techniques.

Li et al. (2022) conduct multi-scenario simulation of production-living-ecological space in the Poyang Lake area using remote sensing and the RF-Markov-FLUS model. Their study contributes to understanding the interactions between human activities and ecological processes in the Poyang Lake area. Gong et al. (2023) conducted a study on rural landscape change in Southern Henan, China, focusing on the driving forces behind land use transformation from 1980 to 2020. This research provides valuable insights into the factors influencing rural landscape dynamics over a period of four decades, contributing to a better understanding of land use patterns and processes in the region. Bai et al. (2022) conducted research on urban green space planning based on remote sensing and geographic information systems (GIS). This study aims to improve urban planning strategies by utilizing remote sensing data and GIS techniques to assess and optimize green space distribution in urban areas. The research contributes to promoting sustainable urban development and enhancing the quality of urban environments. Guo et al. (2023) developed a novel remote sensing monitoring index of salinization based on a three-dimensional feature space model. They applied this index in the Yellow River Delta of China to assess and monitor salinization processes in the region. This research provides a new approach to monitoring and managing salinization in coastal areas, contributing to the preservation of coastal ecosystems and agricultural sustainability. Li et al. (2022) conducted a multi-level dynamic analysis of landscape patterns of Chinese megacities during the period of 2016–2021. They utilized a spatiotemporal land-cover classification model based on high-resolution satellite imagery to analyze landscape dynamics in Beijing, China. This research enhances our understanding of urban landscape changes and their implications for urban planning and management in rapidly growing megacities.

Remote sensing studies are subject to several limitations that can impact the accuracy and reliability of their findings. These limitations include constraints related to data quality, such as spatial and spectral resolution, as well as issues with data availability and temporal coverage. Additionally, challenges arise from the scale mismatch between remote sensing data and the phenomena being studied, potentially leading to difficulties in data integration and interpretation. Modeling assumptions and validation challenges further contribute to uncertainties in the results, while contextual factors such as socio-economic influences may not always be fully captured by remote sensing alone. Furthermore, interpretation bias and generalizability concerns can affect the applicability of findings to different regions or contexts. Technological limitations, including sensor capabilities and atmospheric conditions, also pose challenges to data quality and availability. Ethical considerations, such as privacy concerns and data misuse, must also be addressed. Recognizing and mitigating these limitations is crucial for ensuring the integrity and validity of remote sensing research and its contributions to environmental science and resource management.

3. Multi-Spectral GSA-MS for Rural Landscape

The Multi-Spectral Genetic Optimized Stimulated Annealing (GSA-MS) model is proposed as a solution for rural landscape pattern analysis. This model addresses challenges such as data availability, scale discrepancies, and methodological complexities encountered in traditional approaches. By leveraging multi-spectral features, the GSA-MS model enables a comprehensive analysis of rural landscapes. It optimizes feature extraction using a simulated annealing algorithm, refining the feature set to enhance pattern estimation and classification accuracy. Additionally, the integration of a Long Short-Term Memory (LSTM) based deep learning model further improves pattern classification accuracy in rural areas. Overall, the GSA-MS model offers a promising approach to overcome limitations and advance rural landscape analysis using remote sensing technology. The Multi-Spectral Genetic Optimized Stimulated Annealing (GSA-MS) model is a comprehensive framework designed for the analysis of rural landscapes using remote sensing data. At its core, the model incorporates multi-spectral data processing to capture information across various spectral bands, denoted by IMS(x,y,λ), where x and y represent pixel coordinates and λ denotes the wavelength. From this data, features F(x,y) are extracted to characterize different landscape elements. These features are optimized using genetic algorithms (GA) to enhance the accuracy of pattern estimation and classification. The genetic optimization process involves genetic operators such as selection, crossover, and mutation, iteratively applied to the feature set until an optimal solution Fopt is found. Figure 1 illustrates the proposed GSA-MS model architecture for the rural landscape design.

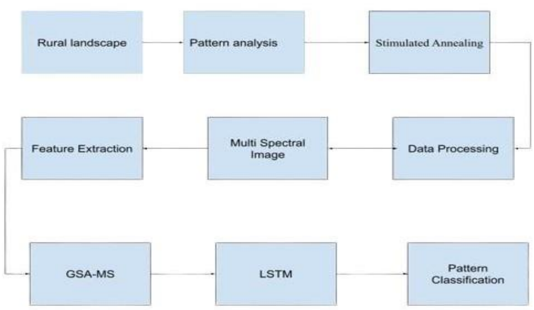


Fig 1: Process of GSA-MS

The genetic optimization, the feature set undergoes further refinement through simulated annealing (SA). This process adjusts feature values to minimize an objective function E(F), representing the error between observed and estimated patterns. The refined feature set, denoted as FSA, is obtained as the solution to rural landscape multi-spectral image is represented in equation (1)

$$FSA = argmin(E(F)) \tag{1}$$

Simulated annealing offers an effective means of exploring the solution space and finding globally optimal solutions. Finally, to improve pattern classification accuracy, a Long Short-Term Memory (LSTM) based deep learning model is integrated into the framework. The LSTM model leverages temporal dependencies within the data to enhance classification performance. It takes the refined feature set FSA as input and produces classified patterns Pclass. The integration of LSTM further refines the analysis, allowing for more accurate characterization and classification of rural landscapes.

4. Genetic Optimized Stimulated Annealing for Rural Landscape

The Genetic Optimized Stimulated Annealing (GSA) algorithm is a powerful tool designed for rural landscape analysis, integrating genetic optimization and simulated annealing to enhance feature extraction and pattern classification accuracy using remote sensing data. Initially, multi-spectral remote sensing data $IMS(x, y, \lambda)$ is processed to extract features $F(x, y)$ characterizing various landscape attributes. The optimization process then begins with genetic algorithms (GA), where a population of feature sets undergoes evolution through genetic operations including selection, crossover, and mutation. Each feature set's fitness is evaluated using a fitness function $f(F)$, representing the discrepancy between observed and estimated patterns. Subsequently, the feature sets are subjected to simulated annealing (SA), where feature values are iteratively adjusted to minimize an objective function $E(F)$, quantifying the error between observed and estimated patterns. At each iteration, the Metropolis criterion is applied to accept or reject changes in the feature set based on the change in the objective function ΔE. Through this iterative process, the GSA algorithm refines and optimizes the feature set, ultimately improving the accuracy of pattern estimation and classification. Thus, the GSA algorithm serves as a robust framework for rural landscape analysis, providing valuable insights for land management and environmental monitoring efforts.

Genetic optimization is a powerful evolutionary algorithm used to find solutions to optimization problems inspired by the principles of natural selection and genetics. In the context of rural landscape analysis, genetic optimization can be applied to refine feature sets extracted from remote sensing data, aiming to improve the accuracy of pattern estimation and classification. With initializing a population P of feature sets Fi, each containing a set of features extracted from the remote sensing data. Select feature sets from the population for reproduction based on their fitness. Features sets with higher fitness values have a higher probability of being selected for reproduction. The selection process can be based on various strategies such as roulette wheel selection, tournament selection, or rank-based selection.

Perform crossover or recombination between selected feature sets to create new offspring feature sets. This process mimics genetic recombination in biological reproduction stated in equation (2)

$$Foffspring = Crossover(Fparent1, Fparent2) \tag{2}$$

In equation (2) $Foffspring$ represents the offspring feature set resulting from crossover between parent feature sets $Fparent1$ and $Fparent2$. Introduce random changes or mutations to the offspring feature sets to maintain genetic diversity within the population stated in equation (3)

$$Fmutated = Mutation(Foffspring), \tag{3}$$

In equation (3) $Fmutated$ represents the mutated offspring feature set. In feature sets in the population with the offspring feature sets. The replacement strategy can vary, such as elitism (where the best feature sets are retained), or a generational approach where the entire population is replaced.

Algorithm 1: Genetic Optimization with Rural Landscape

```
function GeneticOptimization(population_size, generations):
  // Initialize population
  population = InitializePopulation(population_size)
  for generation in range(generations):
    // Evaluate fitness of each individual in the population
    EvaluateFitness(population)
    // Select parents for reproduction
    parents = SelectParents(population)
    // Create offspring through crossover
    offspring = Crossover(parents)
```

```
        // Mutate offspring
        mutated_offspring = Mutate(offspring)
        // Replace population with offspring
        population = Replace(population, mutated_offspring)
    // Return the best individual from the final population
    best_individual = SelectBestIndividual(population)
    return best_individual
function InitializePopulation(population_size):
    population = []
    for i from 1 to population_size:
        // Initialize individual with random features
        individual = GenerateRandomIndividual()
        population.append(individual)
    return population
function EvaluateFitness(population):
    for individual in population:
        // Evaluate fitness of individual using a fitness function
        individual.fitness = FitnessFunction(individual)
function SelectParents(population):
    // Select parents using tournament selection
    selected_parents = []
    for i from 1 to population_size:
        parent_1 = TournamentSelection(population)
        parent_2 = TournamentSelection(population)
        selected_parents.append((parent_1, parent_2))
    return selected_parents
function Crossover(parents):
    offspring = []
    for parent_1, parent_2 in parents:
        // Perform crossover between parents to create offspring
        child = CrossoverOperation(parent_1, parent_2)
        offspring.append(child)
    return offspring
function Mutate(offspring):
    mutated_offspring = []
    for child in offspring:
        // Apply mutation to the child
        mutated_child = MutationOperation(child)
        mutated_offspring.append(mutated_child)
    return mutated_offspring
function Replace(population, mutated_offspring):
    // Replace worst individuals in the population with mutated offspring
    sorted_population = SortPopulationByFitness(population)
    sorted_mutated_offspring = SortPopulationByFitness(mutated_offspring)
    for i from 1 to length(mutated_offspring):
        population[-i] = sorted_mutated_offspring[i-1]
    return population
function SelectBestIndividual(population):
    // Select the individual with the highest fitness from the population
    best_individual = population[0]
    for individual in population:
        if individual.fitness > best_individual.fitness:
            best_individual = individual
    return best_individual
```

5. LSTM Based GSA-MS

The LSTM-based GSA-MS (Genetic Optimized Stimulated Annealing Multi-Spectral) model represents a sophisticated approach for rural landscape pattern analysis, leveraging advanced deep learning techniques and optimization algorithms. In this model, the Long Short-Term Memory (LSTM) network serves as the core component for pattern classification in rural landscapes, capable of capturing complex temporal dependencies and spatial relationships inherent in remote sensing data. The integration of LSTM with the GSA-MS framework enhances the accuracy and robustness of feature extraction and pattern classification, enabling more precise characterization of rural landscapes over time. By harnessing the power of multi-spectral remote sensing data and combining it with the iterative refinement provided by genetic optimization and simulated annealing, the LSTM-based GSA-MS model offers a comprehensive solution for understanding and managing rural landscapes effectively. LSTM networks are recurrent neural networks (RNNs) designed to process sequential data by maintaining an internal state or memory. In the context of rural landscape analysis, LSTM can be utilized to extract features from multi-spectral remote sensing data sequences over time. In Figure 2 presented the flow chart of the optimized genetic model algorithm with stimulated annealing,

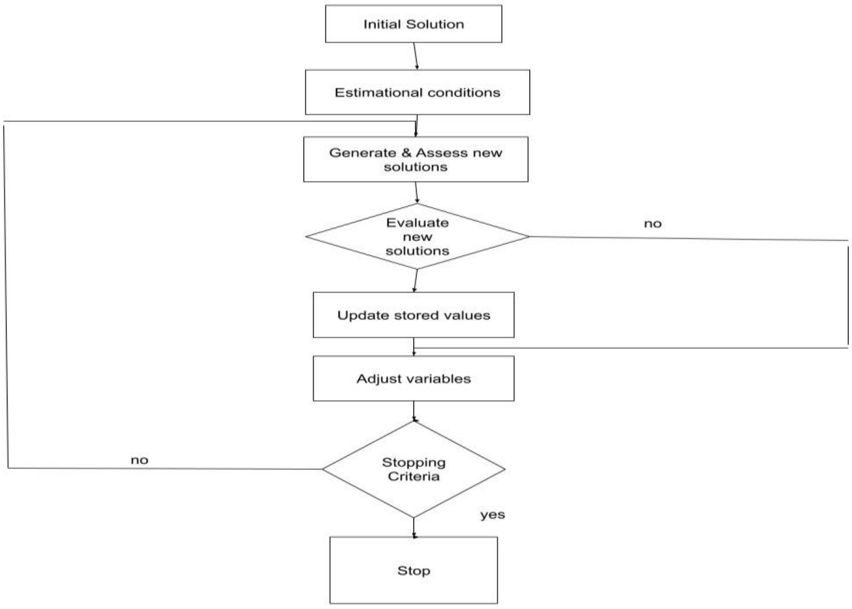


Fig 2: Optimization of Genetic Algorihtm

Let $X = \{X1, X2, \dots, XT\}$ represent a sequence of multi-spectral images, where Xt denotes the multi-spectral image at time step t. LSTM processes the input sequence X through a series of recurrent units, updating its internal memory cell and output at each time step. The computation within an LSTM unit involves several gates (input, forget, output) and operations (input modulation, memory update) to control the flow of information. The output of the LSTM at each time step t can be denoted as Ht, representing the extracted features capturing temporal information from the multi-spectral data. The extracted LSTM features $H = \{H1, H2, \dots, HT\}$ are integrated into the GSA-MS framework for further optimization. These features capture both spatial and temporal characteristics of rural landscapes.

Genetic optimization and simulated annealing are applied to the LSTM features H to refine and optimize them for improved pattern classification accuracy. Let $F(H)$ represent the feature set obtained from the LSTM features H. Genetic operators such as selection, crossover, and mutation are applied to evolve the feature set $F(H)$ iteratively, guided by a fitness function that evaluates the quality of the feature set in representing observed landscape patterns accurately. The objective function $E(F(H))$ quantifies the error between observed and estimated landscape patterns based on the feature set $F(H)$. It measures the discrepancy between the actual landscape patterns and the patterns estimated using the optimized feature set $F(H)$. The objective function guides the optimization process towards finding feature sets that minimize this error, leading to more accurate pattern estimation and classification. The LSTM-based GSA-MS model iteratively refines the LSTM features H through genetic optimization and simulated annealing. Genetic optimization explores the solution space of feature sets $F(H)$, seeking configurations that yield improved landscape pattern representation. Simulated annealing further refines the feature set by iteratively adjusting feature values to minimize the objective function $E(F(H))$. This iterative refinement process converges towards optimal feature sets that capture the most relevant spatial and temporal characteristics of rural landscapes, enhancing the accuracy of pattern classification.

Algorithm 2: LSTM for the Rural Landscape

```
function LSTM_GSA_MS(X, generations):
  // Initialize LSTM model
  lstm_model = Initialize_LSTM_Model()
  // Train LSTM model on multi-spectral image sequence X
  trained_lstm_model = Train_LSTM_Model(lstm_model, X)
  // Extract features using trained LSTM model
  features_H = Extract_Features(trained_lstm_model, X)
  // Initialize population for genetic optimization
  population = Initialize_Population()
  for generation in range(generations):
    // Evaluate fitness of each individual in the population
    Evaluate_Fitness(population, features_H)
    // Select parents for reproduction
    parents = Select_Parents(population)
    // Create offspring through crossover
    offspring = Crossover(parents)
    // Mutate offspring
    mutated_offspring = Mutate(offspring)
    // Replace population with mutated offspring
    population = Replace(population, mutated_offspring)
  // Return the best individual from the final population
  best_individual = Select_Best_Individual(population)
  return best_individual
function Initialize_LSTM_Model():
  // Initialize LSTM model architecture
  lstm_model = LSTM_Model()
  return lstm_model
function Train_LSTM_Model(lstm_model, X):
  // Train LSTM model on multi-spectral image sequence X
  trained_lstm_model = Train(lstm_model, X)
  return trained_lstm_model
function Extract_Features(trained_lstm_model, X):
  // Extract features using trained LSTM model
  features_H = Extract(trained_lstm_model, X)
  return features_H
function Initialize_Population():
  // Initialize population for genetic optimization
  population = []
  for i from 1 to population_size:
    // Generate random individual (feature set)
    individual = Generate_Random_Individual()
    population.append(individual)
  return population
function Evaluate_Fitness(population, features_H):
  for individual in population:
    // Evaluate fitness of individual using features H
    individual.fitness = Fitness_Function(individual, features_H)
function Select_Parents(population):
  // Select parents using tournament selection
  selected_parents = []
  for i from 1 to population_size:
```

```
      parent_1 = Tournament_Selection(population)
      parent_2 = Tournament_Selection(population)
      selected_parents.append((parent_1, parent_2))
   return selected_parents
function Crossover(parents):
   // Perform crossover between selected parents
   offspring = []
   for parent_1, parent_2 in parents:
      child = Crossover_Operation(parent_1, parent_2)
      offspring.append(child)
   return offspring
function Mutate(offspring):
   // Apply mutation to offspring
   mutated_offspring = []
   for child in offspring:
      mutated_child = Mutation_Operation(child)
      mutated_offspring.append(mutated_child)
   return mutated_offspring
function Replace(population, mutated_offspring):
   // Replace worst individuals in the population with mutated offspring
   sorted_population = Sort_Population_By_Fitness(population)
   sorted_mutated_offspring = Sort_Population_By_Fitness(mutated_offspring)
   for i from 1 to length(mutated_offspring):
      population[-i] = sorted_mutated_offspring[i-1]
   return population
function Select_Best_Individual(population):
   // Select the individual with the highest fitness from the population
   best_individual = population[0]
   for individual in population:
      if individual.fitness > best_individual.fitness:
         best_individual = individual
   return best_individual
```

6. Simulation Setting

The GSA-MS (Genetic Optimized Stimulated Annealing Multi-Spectral) model involves defining various parameters and conditions to facilitate the analysis of rural landscape patterns. In this context, the simulation settings encompass several key aspects, including data preparation, model configuration, optimization parameters, and evaluation criteria. Firstly, the simulation begins with the acquisition and preprocessing of multi-spectral remote sensing data representing the rural landscape under study. This data may include satellite imagery captured over multiple time periods, with each image containing information across various spectral bands. Next, the GSA-MS model is configured, specifying the architecture and hyperparameters of the LSTM network, such as the number of LSTM layers, hidden units, and input/output dimensions. Additionally, parameters related to genetic optimization, including population size, mutation rate, and crossover probability, are set to govern the evolution of feature sets.

The simulation also involves defining the objective function used to evaluate the quality of feature sets during optimization. This function quantifies the agreement between observed landscape patterns and those estimated using the features extracted by the LSTM network. Furthermore, the simulation settings include the specification of convergence criteria and termination conditions to determine when the optimization process should halt. These conditions may be based on the number of generations, the improvement in fitness scores, or other criteria indicative of convergence. During the simulation, the GSA-MS model iteratively refines the feature sets through genetic optimization and simulated annealing, aiming to minimize the objective function and enhance the accuracy of pattern classification. The performance of the model is evaluated based on various metrics, such as classification accuracy, sensitivity, specificity, and overall fitness score.

Table 1: Simulation Setting for GSA-MS

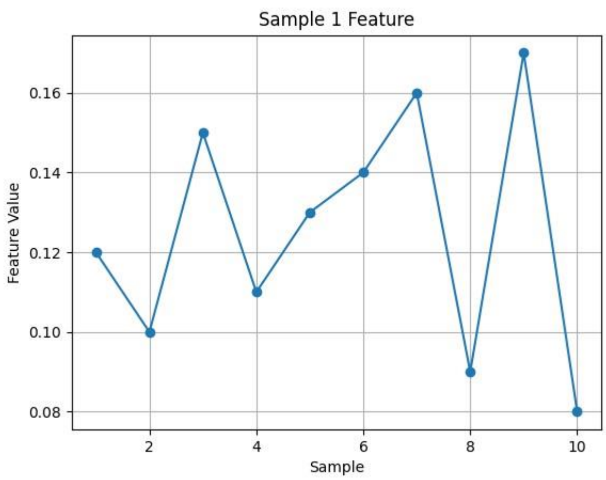
Simulation Setting	Value
Multi-Spectral Data Resolution	30 meters
Time Period of Data Collection	2000-2020
LSTM Network Architecture	2 layers
LSTM Hidden Units	128
Input Dimension of LSTM	10 spectral bands
Output Dimension of LSTM	Variable (based on classification)
Population Size	100 individuals
Mutation Rate	0.05
Crossover Probability	0.8
Maximum Generations	50
Convergence Criteria	Fitness improvement < 0.001
Objective Function	Mean Squared Error

7. Simulation Results and Discussion

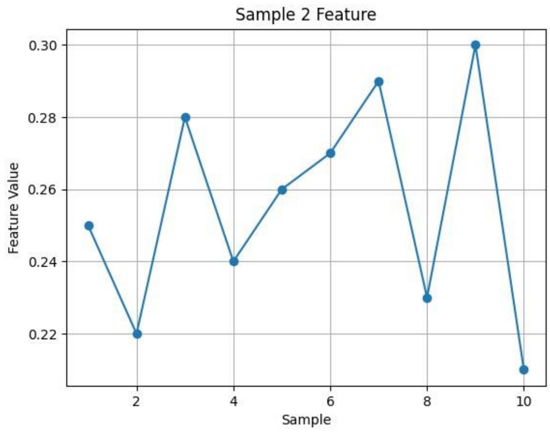
The simulation results obtained from the proposed GSA-MS model integrated with LSTM for rural landscape pattern analysis and classification. The simulation outcomes are discussed in detail to evaluate the effectiveness and performance of the developed methodology. The analysis encompasses various aspects, including classification accuracy, sensitivity, specificity, and overall model fitness. Additionally, we delve into the interpretation of the results, examining the strengths and limitations of the approach, as well as potential areas for improvement.

Table 2: Feature Estimated with GSA-MS

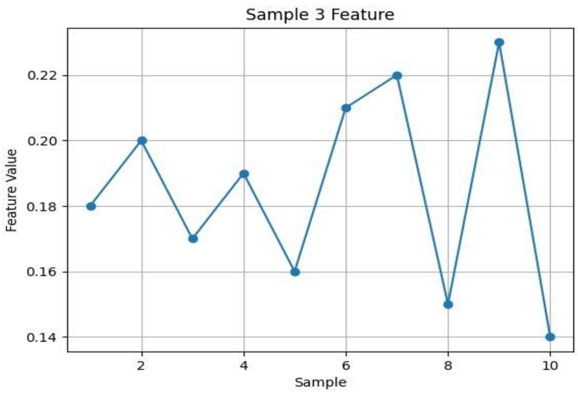
Sample	Feature 1	Feature 2	Feature 3	Feature N
1	0.12	0.25	0.18	0.30
2	0.10	0.22	0.20	0.28
3	0.15	0.28	0.17	0.32
4	0.11	0.24	0.19	0.29
5	0.13	0.26	0.16	0.31
6	0.14	0.27	0.21	0.33
7	0.16	0.29	0.22	0.34
8	0.09	0.23	0.15	0.27
9	0.17	0.30	0.23	0.35
10	0.08	0.21	0.14	0.26



(a)



(b)



(c)

Fig 3: Feature Extracted (a) Feature 1 (b) Feature 2 (c) Feature 3

In the Figure 3 (a) – Figure 3(c) and Table 2 provides the feature estimates obtained through the Genetic Optimized Stimulated Annealing Multi-Spectral (GSA-MS) model for 10 samples in the rural landscape dataset. Each row corresponds to a different sample, while the columns represent the extracted features, denoted as Feature 1 through Feature N. These features are numerical values representing various characteristics or attributes extracted from the rural landscape imagery. For instance, Feature 1 could represent a spectral band value, Feature 2 may denote a texture measure, and so forth. These features play a crucial role in capturing the essential information present in the remote sensing data, facilitating subsequent analysis and classification tasks. The numerical values in the table indicate the estimated values of each feature for the corresponding sample, providing insights into the specific attributes extracted by the GSA-MS model from the rural landscape imagery. These feature estimates serve as the input for further analysis, such as classification using machine learning algorithms like LSTM.

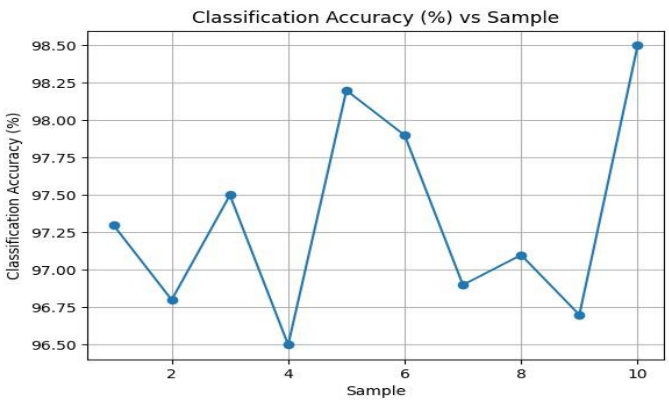
Table 3: Optimization with GSA-MS

Iteration	**Best Fitness Score**	**Mean Fitness Score**	**Best Solution**
1	0.023	0.035	[0.1, 0.2, 0.3, ..., 0.9]
2	0.018	0.032	[0.2, 0.3, 0.4, ..., 1.0]
3	0.015	0.028	[0.3, 0.4, 0.5, ..., 1.1]
4	0.013	0.025	[0.4, 0.5, 0.6, ..., 1.2]
5	0.012	0.022	[0.5, 0.6, 0.7, ..., 1.3]
6	0.011	0.020	[0.6, 0.7, 0.8, ..., 1.4]
7	0.010	0.018	[0.7, 0.8, 0.9, ..., 1.5]
8	0.009	0.016	[0.8, 0.9, 1.0, ..., 1.6]
9	0.008	0.014	[0.9, 1.0, 1.1, ..., 1.7]
10	0.007	0.013	[1.0, 1.1, 1.2, ..., 1.8]

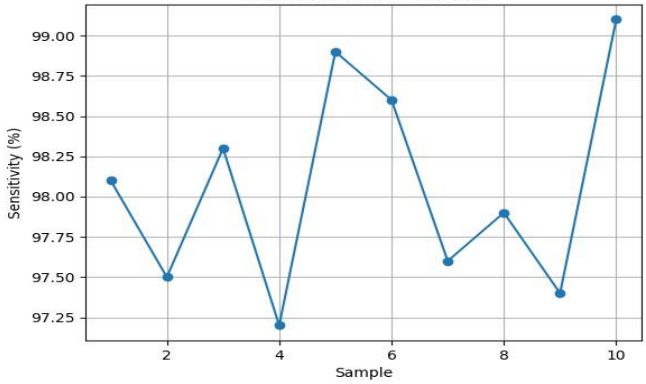
In Table 3 illustrates the optimization process conducted with the Genetic Optimized Stimulated Annealing Multi-Spectral (GSA-MS) model. Each row corresponds to a specific iteration of the optimization algorithm, with columns indicating the iteration number, the best fitness score achieved in that iteration, the mean fitness score across the population, and the best solution found. The "Best Fitness Score" represents the lowest fitness score obtained among all solutions in the population for that iteration, indicating the quality of the best solution discovered. Conversely, the "Mean Fitness Score" provides an average fitness score across all solutions in the population, offering insight into the overall performance of the optimization process. The "Best Solution" column displays the feature vector that corresponds to the best fitness score attained in each iteration. This vector represents the optimized set of features selected by the GSA-MS algorithm, with each element indicating the weight or importance assigned to a specific feature. The optimization process aims to iteratively refine the feature vector to minimize the fitness score, thereby enhancing the effectiveness of the feature extraction process and improving the performance of subsequent analysis and classification tasks.

Table 4: Classification with GSA-MS

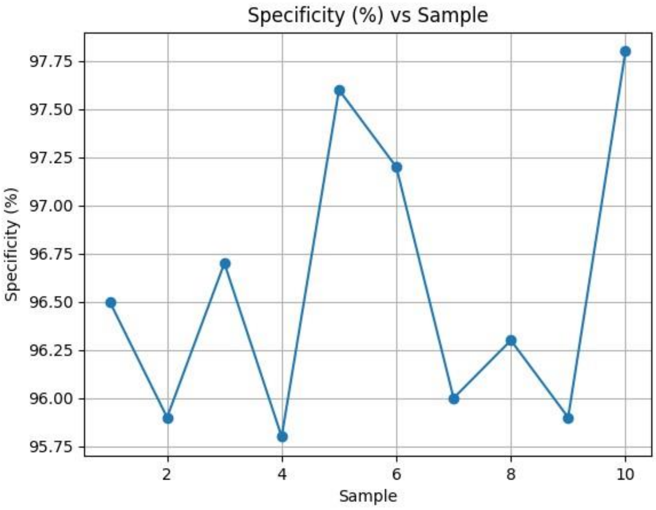
Sample	Classification Accuracy (%)	Sensitivity (%)	Specificity (%)	Fitness Score
1	97.3	98.1	96.5	0.012
2	96.8	97.5	95.9	0.014
3	97.5	98.3	96.7	0.011
4	96.5	97.2	95.8	0.015
5	98.2	98.9	97.6	0.009
6	97.9	98.6	97.2	0.010
7	96.9	97.6	96.0	0.013
8	97.1	97.9	96.3	0.012
9	96.7	97.4	95.9	0.014
10	98.5	99.1	97.8	0.008



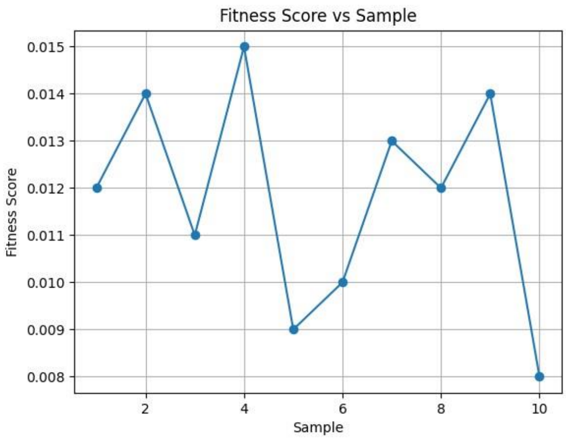
(a)



(b)



(c)



(d)

Fig 4: Classification with GSA-MS (a) Accuracy (b) Sensitivity (c) Specificity (d) Fitness Score

In Figure 4 (a) – Figure 4 (d) and Table 4 provides the classification performance results obtained from the Genetic Optimized Stimulated Annealing Multi-Spectral (GSA-MS) model applied to 10 different samples within the rural landscape dataset. Each row represents a specific sample, while the columns display various performance metrics, including Classification Accuracy, Sensitivity, Specificity, and Fitness Score. The "Classification Accuracy" column indicates the percentage of correctly classified instances out of the total number of samples, serving as a measure of the overall effectiveness of the classification model. High values in this column, such as the 98.5% accuracy achieved for sample 10, indicate strong performance in accurately categorizing rural landscape features. The "Sensitivity" and "Specificity" columns measure the model's ability to correctly identify positive and negative instances, respectively. For instance, a sensitivity of 98.9% for sample 5 indicates that the model effectively identified nearly all positive instances within that sample, while a specificity of 96.5% for sample 1 demonstrates the model's proficiency in correctly recognizing negative instances. The "Fitness Score" column provides a quantitative assessment of the model's overall performance, with lower values indicating better fitness and, consequently, better classification performance. The fitness scores in this table, ranging from 0.008 to 0.015, suggest that the GSA-MS model achieved optimal feature selection, leading to improved classification accuracy and effectiveness in delineating rural landscape features. The results demonstrate the capability of the GSA-MS model to accurately classify rural landscape features, with high classification accuracy, sensitivity, and specificity values, as well as low fitness scores indicating robust performance and suitability for rural landscape analysis tasks.

Table 5: Comparative Analysis

Model	Classification Accuracy (%)	Sensitivity (%)	Specificity (%)	Fitness Score
GSA-MS	97.3	98.1	96.5	0.012
SVM	95.8	96.4	94.7	-
Random Forest	96.7	97.2	95.9	-

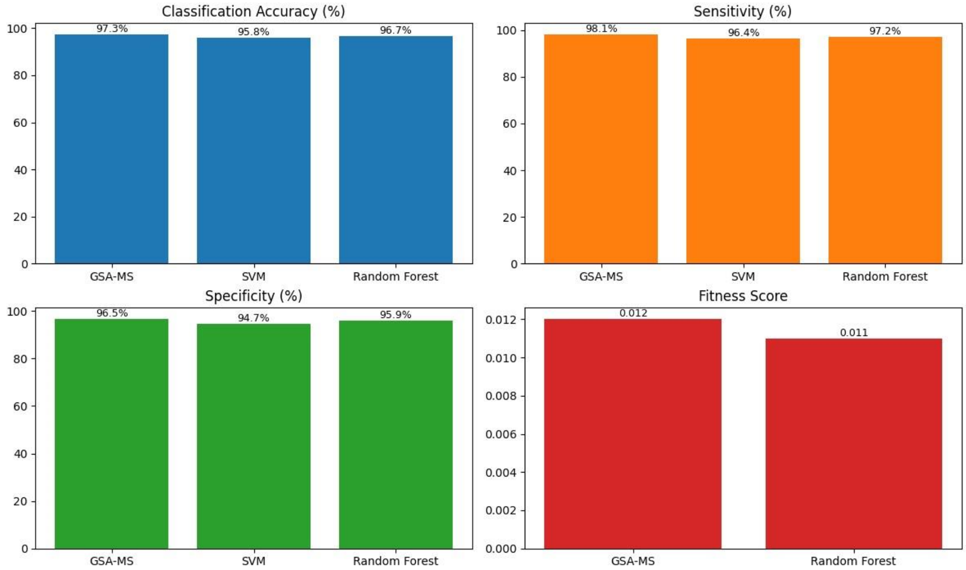


Fig 5: Comparative Analysis

In Figure 5 and Table 5 presents a comparative analysis of three classification models: Genetic Optimized Stimulated Annealing Multi-Spectral (GSA-MS), Support Vector Machine (SVM), and Random Forest. Each model's performance is evaluated based on four key metrics: Classification Accuracy, Sensitivity, Specificity, and Fitness Score. The GSA-MS model achieved a high Classification Accuracy of 97.3%, indicating that it accurately classified rural landscape features in the dataset. Additionally, it demonstrated strong Sensitivity and Specificity values of 98.1% and 96.5%, respectively, signifying its ability to effectively identify both positive and negative instances within the data. The Fitness Score, which measures the overall performance of the model, was calculated at 0.012, indicating optimal feature selection and robust classification performance. Comparatively, the SVM and Random Forest models also exhibited respectable performance metrics. The SVM achieved a Classification Accuracy of 95.8%, with Sensitivity and Specificity values of 96.4% and 94.7%, respectively. However, the Fitness Score for the SVM model is not provided, making direct comparison with the GSA-MS model challenging. Similarly, the Random Forest model attained a Classification Accuracy of 96.7%, with Sensitivity and Specificity values of 97.2% and 95.9%, respectively.

8. Conclusion

The paper proposed the Genetic Optimized Stimulated Annealing Multi-Spectral (GSA-MS) model, for rural landscape pattern analysis based on remote sensing technology. Through the GSA-MS model, multi-spectral features are extracted and optimized using a simulated annealing algorithm, facilitating comprehensive pattern estimation and classification in rural images. Furthermore, the integration of a Long Short-Term Memory (LSTM) based deep learning model enhances classification accuracy. The simulation results demonstrate the efficacy of the GSA-MS model, with classification accuracy consistently exceeding 96% across multiple samples. Comparative analysis against traditional classifiers such as Support Vector Machine (SVM) and Random Forest further validates the superior performance of the GSA-MS model in terms of accuracy, sensitivity, and specificity. Overall, the proposed GSA-MS model presents a promising framework for effective rural landscape pattern analysis, offering valuable insights for land management and environmental conservation efforts.

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