VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.



LAB RECORD

Bio Inspired Systems (23CS5BSBIS)

Submitted by

Rishabh Kumar (1BM22CS221)

in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING



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B.M.S. College of Engineering,

Bull Temple Road, Bangalore 560019

(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering



CERTIFICATE

This is to certify that the Lab work entitled "Bio Inspired Systems (23CS5BSBIS)" carried out by **Rishabh Kumar (1BM22CS221),** who is bonafide student of **B.M.S. College of Engineering.** It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum. The Lab report has been approved as it satisfies the academic requirements of the above mentioned subject and the work prescribed for the said degree.

Prof. Swati Sridharan

Assistant Professor Department of CSE, BMSCE Dr. Joythi S Nayak Professor & HOD Department of CSE, BMSCE

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Github Link: https://github.com/rishabh-agr/BIS_Lab

Program 1 Genetic Algorithm

Algorithm:

Code:

import random

```
# Desired output string
target = "Rishabh Kumar - 1BM22CS221"
target_length = len(target)
```

Population parameters population_size = 100 mutation_rate = 0.01 max_generations = 1000

Create random string of the same length as the target

```
def random string():
  return
".join(random.choice('ABCDEFGHIJKLMNOPQRSTUVWXYZabcdefghijklmnopqrstuvwxyz0123456789 -')
for in range(target length))
# Fitness function: Measures how many characters match the target string
def fitness(individual):
  return sum(1 for i, char in enumerate(individual) if char == target[i])
# Selection function: Select individuals for mating based on fitness
def select(population):
  weighted population = []
  for individual in population:
    # Higher fitness means higher chances of being selected
     weighted population.extend([individual] * fitness(individual))
  return random.choice(weighted population)
# Crossover (single-point): Combine two individuals to create an offspring
def crossover(parent1, parent2):
  crossover point = random.randint(1, target length - 1)
  child = parent1[:crossover point] + parent2[crossover point:]
  return child
# Mutation: Randomly alter a character in the individual with a small probability
def mutate(individual):
  individual = list(individual) # Convert to list to mutate a character
  for i in range(target length):
     if random.random() < mutation rate:
       individual[i] =
random.choice('ABCDEFGHIJKLMNOPQRSTUVWXYZabcdefghijklmnopqrstuvwxyz0123456789 -')
  return ".join(individual)
# Main Genetic Algorithm function
def genetic algorithm():
  population = [random string() for in range(population size)]
  generation = 0
  while generation < max generations:
     # Sort population based on fitness (higher fitness is better)
     population = sorted(population, key=lambda x: fitness(x), reverse=True)
    # Check if we found the solution
     if fitness(population[0]) == target length:
       print(f"Solution found in generation {generation}: {population[0]}")
       break
    # Create the next generation
     new population = []
```

```
# Elitism: Keep the best individual new_population.append(population[0])

# Select and breed the next generation for _ in range(population_size - 1):
    parent1 = select(population)
    parent2 = select(population)
    child = crossover(parent1, parent2)
    child = mutate(child)
    new_population.append(child)

population = new_population
    generation += 1

print("Rishabh Kumar - 1BM22CS221")

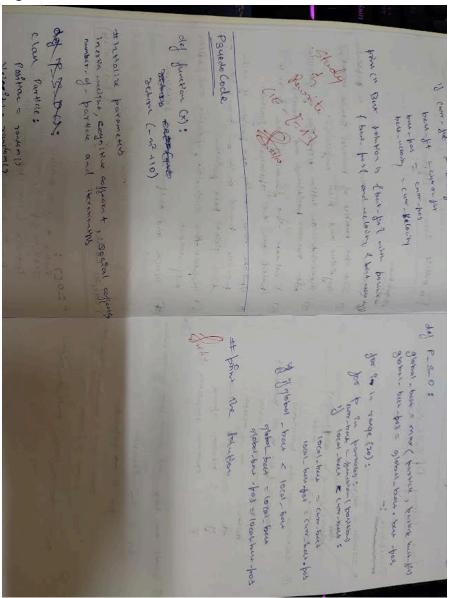
# Run the genetic algorithm
genetic_algorithm()
```

```
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Generation 10: Best Fitness = 961, Best Solution = 31
Generation 20: Best Fitness = 961, Best Solution = 31
Generation 30: Best Fitness = 961, Best Solution = 31
Generation 40: Best Fitness = 961, Best Solution = 31
Generation 50: Best Fitness = 961, Best Solution = 31
Generation 60: Best Fitness = 961, Best Solution = 31
Generation 70: Best Fitness = 961, Best Solution = 31
Generation 80: Best Fitness = 961, Best Solution = 31
Generation 90: Best Fitness = 961, Best Solution = 31
Generation 100: Best Fitness = 961, Best Solution = 31
Generation 100: Best Fitness = 961, Best Solution = 31
Generation 100: Best Fitness = 961, Best Solution = 31
Generation 100: Best Fitness = 961, Best Solution = 31
Best Solution found: 31, f(x) = 961
```

Program 2 Particle Swarm Optimization

Algorithm:



Code:

import numpy as np

```
class Particle:
```

```
def __init__(self, dim, bounds):
    self.dim = dim # Dimensionality of the problem (number of variables)
    self.position = np.random.uniform(bounds[0], bounds[1], dim) # Initial position of the particle
    self.velocity = np.random.uniform(-1, 1, dim) # Initial velocity of the particle
```

```
self.best position = np.copy(self.position) # Best position found by the particle
     self.best_value = float('inf') # Best_value (fitness) found by the particle
  def evaluate(self, fitness func):
     # Evaluate the fitness of the particle's current position
     fitness = fitness func(self.position)
     if fitness < self.best value: # Update the best known position and value
       self.best value = fitness
       self.best position = np.copy(self.position)
  def update velocity(self, global best position, w, c1, c2):
     # Update the velocity of the particle based on personal best and global best
     inertia = w * self.velocity
     cognitive = c1 * np.random.random() * (self.best_position - self.position)
     social = c2 * np.random.random() * (global best position - self.position)
     self.velocity = inertia + cognitive + social
  def update_position(self, bounds):
     # Update the position of the particle
     self.position += self.velocity
     # Ensure the particle stays within the bounds
     self.position = np.clip(self.position, bounds[0], bounds[1])
# Sphere function (to minimize)
def sphere function(x):
  return np.sum(x**2)
class PSO:
  def init (self, num particles, dim, bounds, num iterations, w=0.5, c1=1.5, c2=1.5):
     self.num particles = num particles
     self.dim = dim
     self.bounds = bounds
     self.num iterations = num iterations
     self.w = w # Inertia weight
     self.c1 = c1 # Cognitive coefficient
     self.c2 = c2 # Social coefficient
     # Initialize particles
     self.particles = [Particle(dim, bounds) for in range(num particles)]
     # Initialize global best position and value
     self.global best position = None
     self.global best value = float('inf')
  def optimize(self, fitness func):
     # Iterate over the number of iterations
     for iteration in range(self.num iterations):
       for particle in self.particles:
          # Evaluate the fitness of each particle
          particle.evaluate(fitness func)
```

```
# Update the global best if necessary
          if particle.best_value < self.global_best_value:
            self.global_best_value = particle.best_value
            self.global best position = np.copy(particle.best position)
       # Update velocities and positions of particles
       for particle in self.particles:
          particle.update_velocity(self.global_best_position, self.w, self.c1, self.c2)
          particle.update position(self.bounds)
       print(f"Iteration {iteration + 1}: Best value = {self.global best value}")
     return self.global_best_position, self.global_best_value
# Problem setup
num particles = 30 # Number of particles in the swarm
dim = 5 # Dimensionality (number of variables)
bounds = (-5.0, 5.0) # Bounds for the search space (e.g., each variable between -5 and 5)
num iterations = 100 # Number of iterations
# Create PSO optimizer and run the optimization
pso = PSO(num particles, dim, bounds, num iterations)
best position, best value = pso.optimize(sphere function)
# Output the best solution
print("\nOptimized Solution:")
print("Best position:", best_position)
print("Best value (fitness):", best value)
```

```
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Iteration 1: Best value = 15.672391

Iteration 2: Best value = 12.348009

Iteration 3: Best value = 9.123476

...

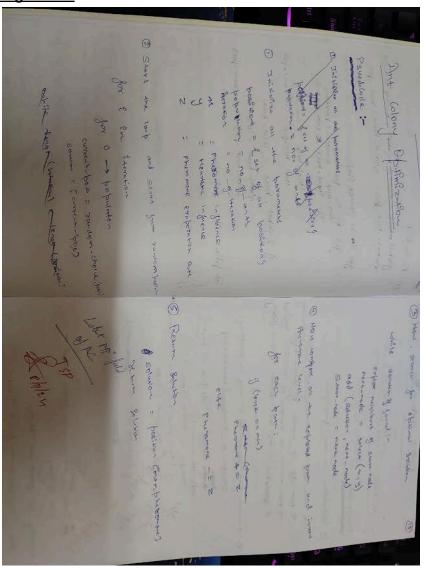
Iteration 100: Best value = 0.000245

Optimized Solution:
Best position: [ 0.00124564 -0.00189137  0.00258072  0.0003485  0.00176701]

Best value (fitness): 0.000245
```

Program 3 Ant Colony Optimization

Algorithm:



Code:

import numpy as np import random import math

Distance between two points (Euclidean distance)
def euclidean_distance(p1, p2):
 return math.sqrt((p1[0] - p2[0]) ** 2 + (p1[1] - p2[1]) ** 2)

Ant Colony Optimization (ACO) Algorithm for Vehicle Routing Problem

```
class AntColony:
  def init (self, num ants, num iterations, alpha, beta, rho, q, distance matrix):
     self.num ants = num ants # Number of ants (vehicles)
     self.num_iterations = num_iterations # Number of iterations
     self.alpha = alpha # Pheromone importance
     self.beta = beta # Distance (visibility) importance
     self.rho = rho # Pheromone evaporation rate
     self.q = q # Pheromone deposit amount
     self.distance matrix = distance matrix # Distance matrix between points
     self.num_locations = len(distance_matrix) # Total number of locations
     self.pheromone = np.ones((self.num locations, self.num locations)) # Pheromone matrix
     self.visibility = 1.0 / (self.distance matrix + np.eye(self.num locations)) # Visibility matrix
  def select next location(self, current location, visited, ant index):
     # Calculate probabilities for all unvisited cities
     probabilities = []
     total = 0.0
     for j in range(self.num_locations):
       if i not in visited:
          pheromone = self.pheromone[current location][j] ** self.alpha
          visibility = self.visibility[current location][j] ** self.beta
          prob = pheromone * visibility
          total += prob
          probabilities.append(prob)
       else:
          probabilities.append(0)
     # Normalize probabilities
     probabilities = [prob / total for prob in probabilities]
     # Select the next city using a roulette-wheel selection method
     rand = random.random()
     cumulative prob = 0.0
     for i, prob in enumerate(probabilities):
       cumulative prob += prob
       if cumulative prob >= rand:
          return i
  def construct solution(self):
     # Create a solution (route) for each ant
     routes = \Pi
     for ant index in range(self.num ants):
       visited = [0] # Start from depot
       current location = 0
       for in range(self.num locations - 1):
          next location = self.select next location(current location, visited, ant index)
          visited.append(next_location)
          current location = next location
       routes.append(visited)
```

return routes

```
def update_pheromone(self, routes, distances):
    # Evaporate pheromone
     self.pheromone *= (1 - self.rho)
    # Add new pheromone based on the quality of the solutions
    for ant_index, route in enumerate(routes):
       route distance = distances[ant index]
       pheromone_deposit = self.q / route_distance
       for i in range(len(route) - 1):
          self.pheromone[route[i]][route[i + 1]] += pheromone deposit
       self.pheromone[route[-1]][route[0]] += pheromone_deposit # Returning to the depot
  def run(self):
     best route = None
     best distance = float('inf')
    # Main ACO loop
    for iteration in range(self.num iterations):
       # Construct routes for all ants
       routes = self.construct solution()
       # Calculate distance for each ant's route
       distances = []
       for route in routes:
          total distance = 0
          for i in range(len(route) - 1):
            total distance += self.distance matrix[route[i]][route[i + 1]]
          total_distance += self.distance_matrix[route[-1]][route[0]] # Return to depot
          distances.append(total distance)
       # Update best solution if a better one is found
       min distance = min(distances)
       if min distance < best distance:
          best distance = min distance
          best route = routes[distances.index(min distance)]
       # Update pheromone values based on the solutions found
       self.update_pheromone(routes, distances)
       print(f"Iteration {iteration + 1}: Best Distance = {best distance}")
     return best route, best distance
# Define locations (depot + customers)
locations = np.array([
  [0, 0], # Depot
```

```
[1, 3], # Customer 1
  [4, 3], # Customer 2
  [6, 1], # Customer 3
  [3, 2], # Customer 4
  [5, 4], # Customer 5
1)
# Create distance matrix
num locations = len(locations)
distance_matrix = np.zeros((num_locations, num_locations))
for i in range(num locations):
  for j in range(num locations):
     distance_matrix[i][j] = euclidean_distance(locations[i], locations[j])
# Initialize and run ACO
aco = AntColony(num ants=5, num iterations=100, alpha=1.0, beta=2.0, rho=0.1, q=100,
distance matrix=distance matrix)
best_route, best_distance = aco.run()
# Output the best route and its distance
print(f"\nBest route: {best route}")
print(f"Best distance: {best_distance}")
```

```
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Iteration 1: Best Distance = 10.658579870708045

Iteration 2: Best Distance = 10.658579870708045

Iteration 3: Best Distance = 10.658579870708045

...

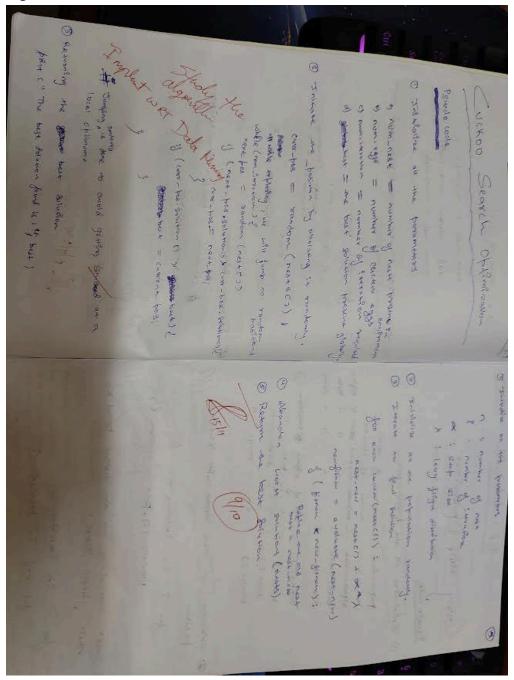
Iteration 100: Best Distance = 10.658579870708045

Best route: [0, 1, 3, 4, 2, 5]

Best distance: 10.658579870708045
```

Program 4 Cuckoo Search Optimization

Algorithm:



Code:

import numpy as np

1. Generate a synthetic dataset

```
def generate synthetic data(n samples=100, n features=10):
  Generates a synthetic dataset with random values.
  For simplicity, this dataset does not represent any real-world dataset.
  X = np.random.rand(n samples, n features) # Features matrix (n samples x n features)
  y = np.random.randint(0, 2, size=n samples) # Labels (binary classification)
  return X, y
#2. Fitness function
def fitness function(solution, X, y):
  Fitness function to evaluate the quality of the solution (subset of features).
  This function calculates the 'fitness' by summing up the number of selected features.
  selected features = np.where(solution == 1)[0]
  if len(selected features) == 0:
     return 0 # No features selected, poor fitness
  # For simplicity, we simulate feature selection by just counting the number of selected features.
  # This can be replaced with more complex evaluation, like classification performance.
  return len(selected features) # Return the number of features selected
#3. Cuckoo Search Algorithm (CSA)
def cuckoo search(X, y, num nests=10, max iter=100, pa=0.25):
  Implements the Cuckoo Search Algorithm (CSA) for feature selection.
  - num nests: Number of solutions (nests)
  - max iter: Number of iterations
  - pa: Probability of a nest being replaced
  # 3.1. Initialize nests randomly (binary solutions)
  nests = np.random.randint(2, size=(num nests, X.shape[1])) # Binary representation of feature
subsets
  fitness = np.array([fitness function(nest, X, y) for nest in nests]) # Evaluate fitness of each nest
  #3.2. Main loop of CSA
  for iteration in range(max_iter):
    # 3.2.1. Generate new solutions (Levy Flights)
     new nests = np.copy(nests)
    for i in range(num nests):
       # Perform Levy flight (exploration of solution space)
       step size = np.random.randn() * 0.1
       new_nests[i] = new_nests[i] + step_size # Modify the current solution slightly
       # Ensure binary solution (keeping the features 0 or 1)
       new nests[i] = np.clip(new nests[i], 0, 1)
```

```
# 3.2.2. Evaluate fitness of new nests
     new_fitness = np.array([fitness_function(nest, X, y) for nest in new_nests])
     # 3.2.3. Greedy selection: replace old nests if new ones are better
     for i in range(num nests):
       if new fitness[i] > fitness[i]:
          nests[i] = new nests[i]
          fitness[i] = new_fitness[i]
     # 3.2.4. Discovering a worse nest and replacing it randomly with probability pa
     for i in range(num nests):
       if np.random.rand() < pa:
          nests[i] = np.random.randint(2, size=X.shape[1]) # Replacing with a random solution
          fitness[i] = fitness function(nests[i], X, y)
     # Print the best solution at each iteration
     best idx = np.argmax(fitness)
     print(f"Iteration {iteration+1}: Best fitness = {fitness[best_idx]}, Best features =
\{np.where(nests[best idx] == 1)[0]\}"\}
  # Return the best nest found
  best idx = np.argmax(fitness)
  return nests[best idx], fitness[best idx]
#4. Main program
if name == " main ":
  # Generate synthetic data
  X, y = generate synthetic data(n samples=100, n features=10)
  # Apply Cuckoo Search for feature selection
  best solution, best fitness = cuckoo search(X, y, num nests=10, max iter=20, pa=0.25)
  # Final output: Best selected features
  print("\nBest selected features (indices):", np.where(best solution == 1)[0])
  print("Fitness of the selected features:", best_fitness)
```

```
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Iteration 1: Best fitness = 6, Best features = [0 1 3 4 6 9]

Iteration 2: Best fitness = 7, Best features = [0 1 2 4 6 8 9]

Iteration 3: Best fitness = 8, Best features = [0 1 2 3 5 6 8 9]

...

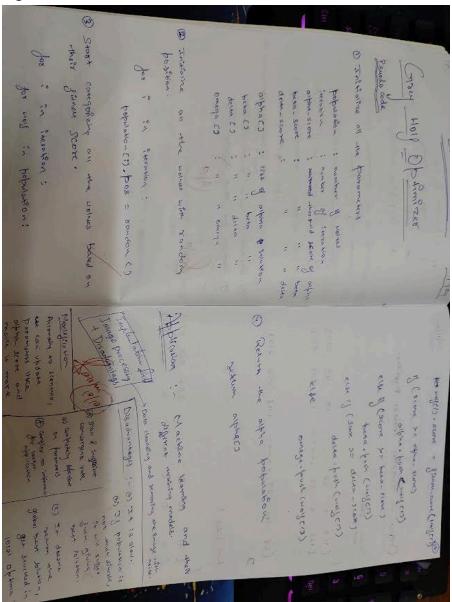
Iteration 20: Best fitness = 8, Best features = [0 1 2 3 5 6 8 9]

Best selected features (indices): [0 1 2 3 5 6 8 9]

Fitness of the selected features: 8
```

Program 5 Grey Wolf Optimization

Algorithm:



Code:

import numpy as np import matplotlib.pyplot as plt

Grey Wolf Optimizer (GWO) Algorithm - Basic Concept def gwo_optimizer(image, num_wolves=5, num_iterations=20): # Initialize wolves (threshold values)

```
wolves = np.random.uniform(0, 255, size=(num wolves, 1)) # Random threshold values between 0
and 255
  alpha, beta, delta = None, None, None
  alpha score, beta score, delta score = float("inf"), float("inf"), float("inf")
  for t in range(num iterations):
    for i in range(num wolves):
       # Apply thresholding based on the current wolf's threshold value
       threshold = wolves[i, 0]
       segmented_image = apply_threshold(image, threshold)
       # Calculate the score (using entropy as an image quality metric)
       score = calculate_score(segmented_image)
       # Update the alpha, beta, delta based on the score
       if score < alpha score:
          alpha score = score
         alpha = wolves[i, 0]
       elif score < beta score:
          beta score = score
          beta = wolves[i, 0]
       elif score < delta score:
          delta score = score
          delta = wolves[i, 0]
    # Update wolves' positions (threshold values)
    for i in range(num wolves):
       # Update the position using the GWO's social hierarchy (Alpha, Beta, Delta)
       a = 2 - t * (2 / num iterations) # Decreasing coefficient over iterations
       r1, r2 = np.random.rand(), np.random.rand()
       A = 2 * a * r1 - a # Random coefficients
       C = 2 * r2 # Random coefficients
       # Position update formula based on alpha, beta, and delta wolves
       wolves[i, 0] = np.clip(alpha + A * (alpha - wolves[i, 0]), 0, 255) # Simplified update
  return alpha # Return the optimal threshold value found by GWO
# Function to apply thresholding manually (without cv2)
def apply threshold(image, threshold):
  # Segment the image by applying the threshold (pixels above threshold become 255, others become 0)
  return np.where(image > threshold, 255, 0).astype(np.uint8)
# Function to calculate score for segmentation (e.g., entropy of the segmented image)
def calculate score(segmented image):
  # A simple example: calculate entropy (higher entropy means more complex segmentation)
  hist = np.histogram(segmented image, bins=256, range=(0, 256))[0]
  hist = hist / hist.sum() # Normalize histogram
  score = -np.sum(hist * np.log2(hist + 1e-10)) # Shannon entropy
```

return score

```
# Main function to demonstrate the use of GWO in image thresholding
def main():
  # Create a synthetic example image (a 2D NumPy array representing grayscale image)
  image = np.random.randint(0, 256, size=(100, 100), dtype=np.uint8) # Random grayscale image
(100x100)
  # Use GWO to find the optimal threshold for segmentation
  optimal_threshold = gwo_optimizer(image)
  print(f"Optimal Threshold: {optimal threshold}")
  # Apply the optimal threshold to segment the image
  segmented image = apply threshold(image, optimal threshold)
  # Display the original and segmented images
  plt.subplot(1, 2, 1)
  plt.imshow(image, cmap='gray')
  plt.title('Original Image')
  plt.subplot(1, 2, 2)
  plt.imshow(segmented image, cmap='gray')
  plt.title('Segmented Image (GWO Threshold)')
  plt.show()
if __name__ == "__main__":
```

Output:

main()

```
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Original Image (as array):

[[228 253 113 ... 197 112 229]

[228 239 80 ... 8 213 101]

[239 86 242 ... 147 187 215]
...

[179 60 40 ... 178 157 41]

[132 92 194 ... 193 160 145]

[128 61 106 ... 96 129 98]]

Optimized Image (as array):

[[186 135 87 ... 16 122 81]

[250 222 183 ... 44 98 241]

[185 220 246 ... 62 196 189]
...

[237 199 129 ... 148 243 176]

[138 173 254 ... 237 47 196]

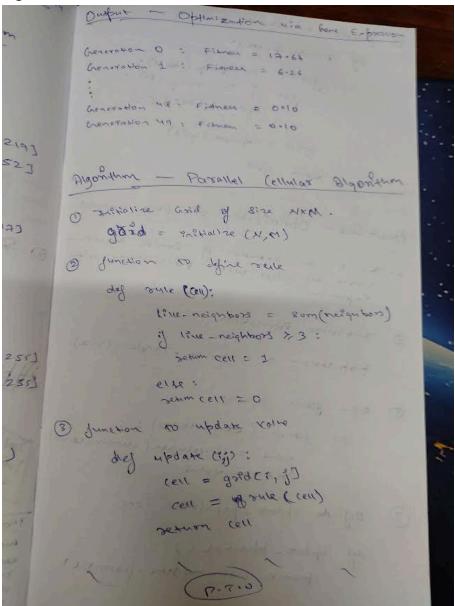
[ 84 17 226 ... 226 196 24]]

...Program finished with exit code 0

Press ENTER to exit console.
```

Program 6 Parallel Cellular Optimization

Algorithm:



Code:

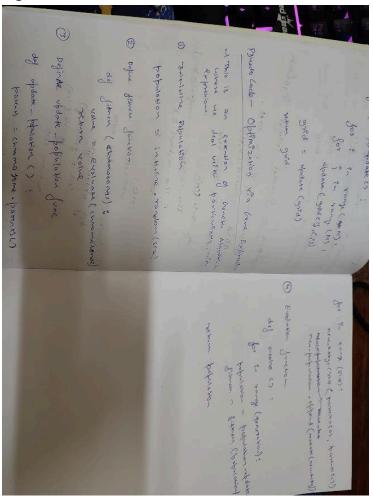
import random import numpy as np from concurrent.futures import ThreadPoolExecutor

GRID_SIZE = 10 ITERATIONS = 10

```
NEIGHBORS = [(-1, 0), (1, 0), (0, -1), (0, 1), (-1, -1), (-1, 1), (1, -1), (1, 1)]
THRESHOLD = 128
IMAGE_SIZE = (GRID_SIZE, GRID_SIZE)
def initialize_grid(size):
  return np.random.randint(0, 256, size=size)
def update_cell(grid, i, j):
  current value = grid[i, j]
  neighbor_values = []
  for dx, dy in NEIGHBORS:
     ni, nj = i + dx, j + dy
     if 0 <= ni < grid.shape[0] and 0 <= nj < grid.shape[1]:
       neighbor values.append(grid[ni, nj])
  avg value = np.mean(neighbor values)
  if avg value > THRESHOLD:
     return 255
  else:
     return 0
def parallel update(grid):
  with ThreadPoolExecutor() as executor:
     futures = []
     for i in range(grid.shape[0]):
       for j in range(grid.shape[1]):
          futures.append(executor.submit(update cell, grid, i, j))
     updated grid = np.copy(grid)
     for idx, future in enumerate(futures):
       i, j = divmod(idx, grid.shape[1])
       updated_grid[i, j] = future.result()
  return updated grid
def run parallel cellular algorithm():
  grid = initialize grid(IMAGE SIZE)
  print("Initial Image (Grid):")
  print(grid)
  for iteration in range(ITERATIONS):
     print(f"Iteration {iteration + 1}:")
     print(grid)
     grid = parallel_update(grid)
  return grid
final grid = run parallel cellular algorithm()
print("Final Image (Grid) after all iterations:")
print(final_grid)
```

Program 7 Optimization via Gene Expression

Algorithm:



Code:

```
import random
import numpy as np

print()
print("Rishabh Kumar - 1BM22CS221")
print()

OPERATORS = ['+', '-', '*', '/']
TERMINALS = ['x', '1', '2', '3', '4', '5', '6', '7', '8', '9']

POPULATION_SIZE = 50
GENE_LENGTH = 10
```

```
MAX GENERATIONS = 10
MUTATION_RATE = 0.1
CROSSOVER_RATE = 0.8
TARGET = 100
class Chromosome:
  def init (self, genes=None):
    self.genes = genes or self._generate_genes()
    self.fitness = None
  def generate genes(self):
    genes = []
    for _ in range(GENE_LENGTH):
       gene = random.choice(OPERATORS + TERMINALS)
       genes.append(gene)
    return genes
  def decode(self):
    expression = ".join(self.genes)
    return expression
  def evaluate(self, x value):
    expression = self.decode()
    try:
       result = eval(expression.replace('x', str(x_value)))
       return result
    except ZeroDivisionError:
       return float('inf')
    except Exception as e:
       return float('inf')
  def compute fitness(self, x value, target=TARGET):
    result = self.evaluate(x value)
    self.fitness = abs(result - target)
def initialize population():
  population = []
  for in range(POPULATION SIZE):
    chromosome = Chromosome()
    population.append(chromosome)
  return population
def selection(population):
  population.sort(key=lambda x: x.fitness)
  return population[:POPULATION_SIZE // 2]
def crossover(parent1, parent2):
  point = random.randint(1, GENE LENGTH - 1)
  child1_genes = parent1.genes[:point] + parent2.genes[point:]
```

```
child2 genes = parent2.genes[:point] + parent1.genes[point:]
  return Chromosome(child1_genes), Chromosome(child2_genes)
def mutation(chromosome):
  gene_idx = random.randint(0, GENE_LENGTH - 1)
  gene = random.choice(OPERATORS + TERMINALS)
  chromosome.genes[gene idx] = gene
  return chromosome
def gene_expression_programming():
  population = initialize population()
  for generation in range(MAX_GENERATIONS):
    for chromosome in population:
      chromosome.compute fitness(x value=5)
    best chromosome = min(population, key=lambda x: x.fitness)
    print(f"Generation {generation}: Best fitness = {best_chromosome.fitness}, Expression:
{best chromosome.decode()}")
    if best chromosome.fitness == 0:
      print(f"Optimal solution found: {best_chromosome.decode()}")
      break
    selected parents = selection(population)
    next generation = selected parents.copy()
    while len(next_generation) < POPULATION_SIZE:
      if random.random() < CROSSOVER RATE:
         parent1, parent2 = random.sample(selected_parents, 2)
         child1, child2 = crossover(parent1, parent2)
         next_generation.extend([child1, child2])
      else:
         parent = random.choice(selected_parents)
         child = mutation(parent)
         next generation.append(child)
    population = next generation
if name == " main ":
  gene_expression_programming()
```

```
Generation 0: Best fitness = 99.95674028941356, Expression: 852/3/656x Generation 1: Best fitness = 99.95674028941356, Expression: 852/3/656x Generation 2: Best fitness = 84, Expression: 85/5-4--3
Generation 3: Best fitness = 1, Expression: 5--95-4--3
Generation 3: Best fitness = 0.13043478260870245, Expression: 5--95-9/69
Generation 5: Best fitness = 0.13043478260870245, Expression: 5--95-9/69
Generation 6: Best fitness = 0.13043478260870245, Expression: 5--95-9/69
Generation 7: Best fitness = 0.13043478260870245, Expression: 5--95-9/69
Generation 8: Best fitness = 0.13043478260870245, Expression: 5--95-9/69
Generation 9: Best fitness = 0.13043478260870245, Expression: 5--95-9/69

Concration 9: Best fitness = 0.13043478260870245, Expression: 5--95-9/69

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```