VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB RECORD

Bio Inspired Systems (23CS5BSBIS)

Submitted by

Srushti Sunkad (1BM23CS341)

in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
(Autonomous Institution under VTU)
BENGALURU-560019
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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 **Srushti Sunkad (1BM23CS341),** 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.

Rohith Vaidya K Assistant Professor Department of CSE, BMSCE	Dr. Kavitha Sooda Professor & HOD Department of CSE, BMSCE

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Github Link:

https://github.com/srushtinagaraju/BIS-Lab-1BM24CS424.git

Program 1

Genetic Algorithm for Optimization Problems:

Genetic Algorithms (GA) are inspired by the process of natural selection and genetics, where the fittest individuals are selected for reproduction to produce the next generation. GAs are widely used for solving optimization and search problems. Implement a Genetic Algorithm using Python to solve a basic optimization problem, such as finding the maximum value of a mathematical function.

Implementation Steps:
1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the population size, mutation rate, crossover rate, and number of generations.
3. Create Initial Population: Generate an initial population of potential solutions.
4. Evaluate Fitness: Evaluate the fitness of each individual in the population.
5. Selection: Select individuals based on their fitness to reproduce.
6. Crossover: Perform crossover between selected individuals to produce offspring.
7. Mutation: Apply mutation to the offspring to maintain genetic diversity.
8. Iteration: Repeat the evaluation, selection, crossover, and mutation processes for a fixed number of generations or until convergence criteria are met.
9. Output the Best Solution: Track and output the best solution found during the generations.

Algorithm:

29/08/25

Bafna Gold
Date: Page:

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① Genetic Algorithm : 5 main phases - Initialization
- fitness Assignment
- Selection
- crossover
- Termination

Steps:
① Selecting coding technique
0 to 31

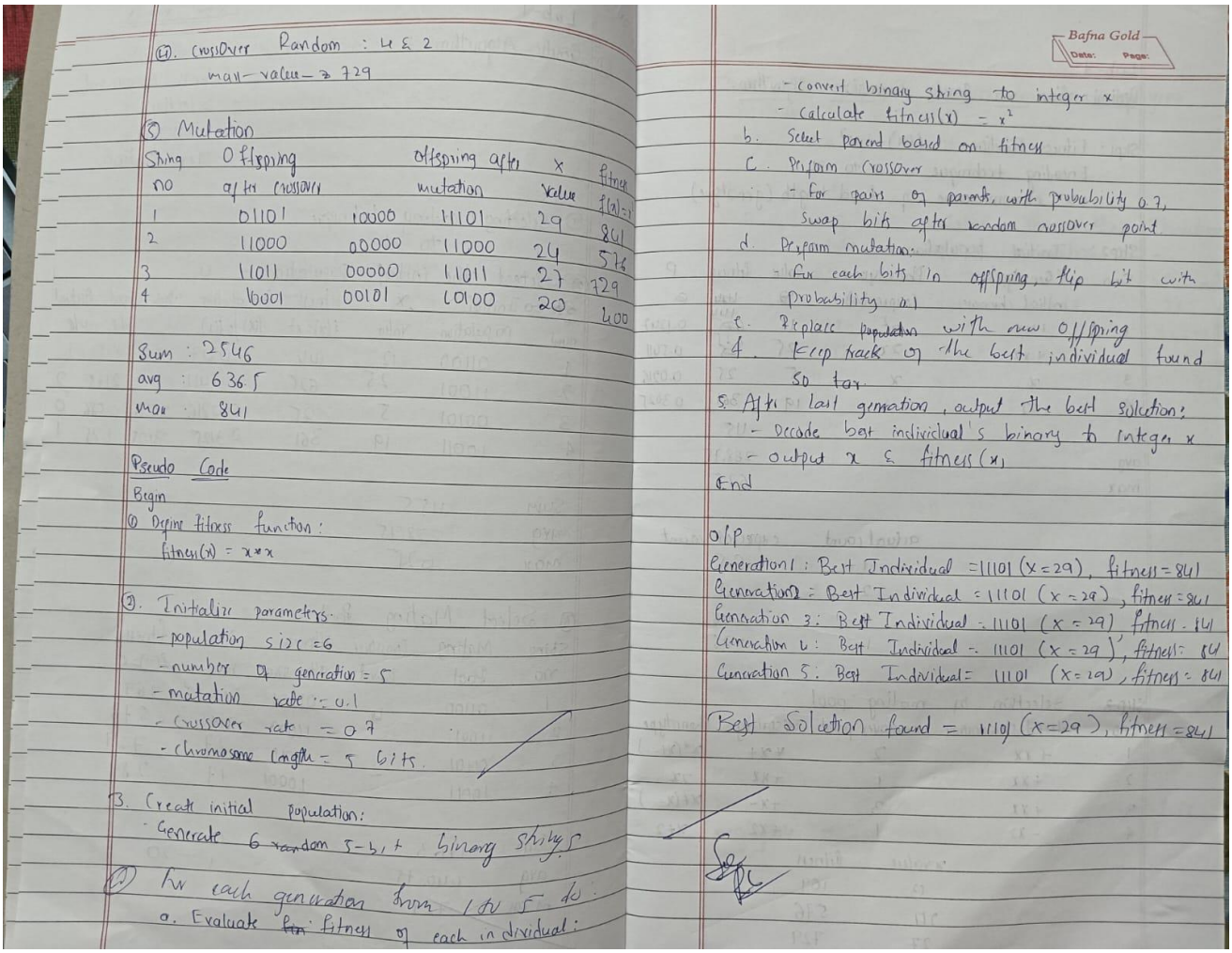
② Select the initial population - 4

String no	Initial Population	x Value	fitness $f(x)=x^2$	Probability $f(x)/\Sigma f(x)$	% Prob	Expect Count	Actual Count
1	01100	12	144	0.1247	12.47	0.49	1
2	11001	25	625	0.5411	54.11	2.165	2
3	00101	5	25	0.0216	2.16	0.086	0
4	10011	19	361	0.3125	31.25	1.25	1
Sum		1155					
avg		288.75					
max		625					

③. Select Mating Pool

String no.	Mating Pool	Crossover Point	Offspring after crossover	x value	fitness $f(x)=x^2$
1	01100	4	01101	13	169
2	11001		11000	24	576
3	00101	2	00111	27	729
4	10011		10001	17	289
Sum		1763			
avg		440.75			
max		729			

0 → 1
1 → 0



Code:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Creating a sample dataset
X, y = make_classification(n_samples=500, n_features=10, n_informative=8, n_classes=2)
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2)

# Neural Network Structure
input_size = X.shape[1]
hidden_size = 5
output_size = 1

# Helper functions for the Neural Network
```

```
def sigmoid(x):
    return 1 / (1 + np.exp(-x))
def forward_pass(X, weights1, weights2):
    hidden_input = np.dot(X, weights1)
    hidden_output = sigmoid(hidden_input)
    output_input = np.dot(hidden_output, weights2)
    output = sigmoid(output_input)
    return output
def compute_fitness(weights):
    predictions = forward_pass(X_train, weights['w1'], weights['w2'])
    predictions = (predictions > 0.5).astype(int)
    accuracy = accuracy_score(y_train, predictions)
    return accuracy
# Genetic Algorithm Parameters
population_size = 20
generations = 10
mutation_rate = 0.1

# Initialize Population
population = []
for _ in range(population_size):
    individual = {
        'w1': np.random.randn(input_size, hidden_size),
        'w2': np.random.randn(hidden_size, output_size)
    }
    population.append(individual)

# Tracking performance
best_fitness_history = []
average_fitness_history = []

# Main Genetic Algorithm Loop
for generation in range(generations):
    # Evaluate Fitness of each Individual
    fitness_scores = np.array([compute_fitness(individual) for individual in population])
    best_fitness = np.max(fitness_scores)
    average_fitness = np.mean(fitness_scores)
    best_fitness_history.append(best_fitness)
    average_fitness_history.append(average_fitness)

    # Selection: Select top half of the population
    sorted_indices = np.argsort(fitness_scores)[::-1]
    population = [population[i] for i in sorted_indices[:population_size//2]]
   # Crossover and Mutation
    new_population = []
    while len(new_population) < population_size:
        parents = np.random.choice(population, 2, replace=False)
```

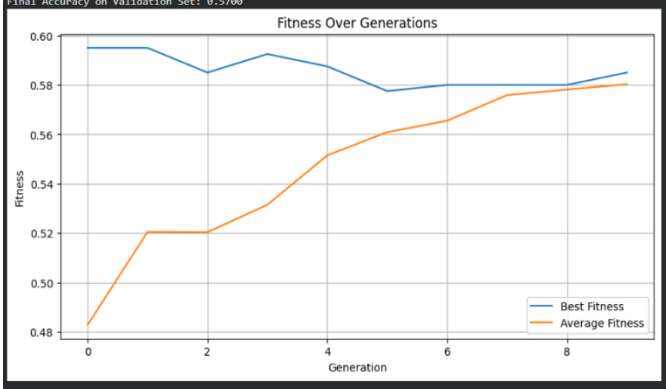
```
        child = {
            'w1': (parents[0]['w1'] + parents[1]['w1']) / 2,
            'w2': (parents[0]['w2'] + parents[1]['w2']) / 2
        }
        # Mutation
        if np.random.rand() < mutation_rate:
            child['w1'] += np.random.randn(*child['w1'].shape) * 0.1
            child['w2'] += np.random.randn(*child['w2'].shape) * 0.1
        new_population.append(child)
    population = new_population
print(f"Generation {generation+1}, Best Fitness: {best_fitness:.4f}")

# Evaluate the best individual on validation set
best_individual = population[np.argmax(fitness_scores)]
predictions = forward_pass(X_val, best_individual['w1'], best_individual['w2'])
predictions = (predictions > 0.5).astype(int)
final_accuracy = accuracy_score(y_val, predictions)
print(f"Final Accuracy on Validation Set: {final_accuracy:.4f}")
# Plotting the results
plt.figure(figsize=(10, 5))
plt.plot(best_fitness_history, label='Best Fitness')
plt.plot(average_fitness_history, label='Average Fitness')
plt.title('Fitness Over Generations')
plt.xlabel('Generation')
plt.ylabel('Fitness')
plt.legend()
plt.grid(True)
plt.show()
```

OUTPUT:

```
Generation 1, Best Fitness: 0.5950
Generation 2, Best Fitness: 0.5950
Generation 3, Best Fitness: 0.5850
Generation 4, Best Fitness: 0.5925
Generation 5, Best Fitness: 0.5875
Generation 6, Best Fitness: 0.5775
Generation 7, Best Fitness: 0.5800
Generation 8, Best Fitness: 0.5800
Generation 9, Best Fitness: 0.5800
Generation 10, Best Fitness: 0.5850
Final Accuracy on Validation Set: 0.5700
```

colab.research.google.com – To exit full screen, press Esc



Program 2

Particle Swarm Optimization for Function Optimization:

Particle Swarm Optimization (PSO) is inspired by the social behavior of birds flocking or fish schooling. PSO is used to find optimal solutions by iteratively improving a candidate solution with regard to a given measure of quality. Implement the PSO algorithm using Python to optimize a mathematical function.
Implementation Steps:
1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the number of particles, inertia weight, cognitive and social coefficients.
3. Initialize Particles: Generate an initial population of particles with random positions and velocities.
4. Evaluate Fitness: Evaluate the fitness of each particle based on the optimization function.
5. Update Velocities and Positions: Update the velocity and position of each particle based on its own best position and the global best position.
6. Iterate: Repeat the evaluation, updating, and position adjustment for a fixed number of iterations or until convergence criteria are met.
7. Output the Best Solution: Track and output the best solution found during the iterations.

Algorithm:

12/09/25.

Lab-3

Bafna Gold
Date: Page:

2) Particle Swarm Optimization

1. P = particle initialization();
2. for i = 1 to max
3. for each particle p in P do
   fp = f(P)
4. If fp is better than f(pbest)
   pbest = p;
5. end
6. end
7. gbest = best p in P
8. for each particle p in P do
9. $v_i^{t+1} = \underbrace{v_i^t}_{\text{inertia}} + c_1 \underbrace{U_1^t (pb_i^t - p_i^t)}_{\text{personal influence}} + c_2 \underbrace{U_2^t (gb^t - p_i^t)}_{\text{social influence}}$
10. $p_i^{t+1} = p_i^t + v_i^{t+1}$
11. end
12. end

Output,

Iteration 115, Best CV Accuracy : 0.9807, Best c : 8.0937
Iteration 215, Best CV Accuracy : 0.9867, Best c : 8.0937
Iteration 315

4

5

Final

Code:

```
import random

# Define the function to optimize
def objective_function(position):
    x, y = position
    return x**2 + y**2

# PSO parameters
num_particles = 30
num_dimensions = 2
max_iterations = 10   # Changed from 100 to 10

w = 0.5
c1 = 1.5
c2 = 1.5

# Initialize particles
particles = []
velocities = []
personal_best_positions = []
personal_best_scores = []

for _ in range(num_particles):
    position = [random.uniform(-10, 10) for _ in range(num_dimensions)]
    velocity = [random.uniform(-1, 1) for _ in range(num_dimensions)]
    particles.append(position)
    velocities.append(velocity)
    personal_best_positions.append(position[:])
    personal_best_scores.append(objective_function(position))

global_best_index = personal_best_scores.index(min(personal_best_scores))
global_best_position = personal_best_positions[global_best_index][:]
global_best_score = personal_best_scores[global_best_index]

for iteration in range(max_iterations):
    for i in range(num_particles):
        for d in range(num_dimensions):
            r1 = random.random()
            r2 = random.random()

            velocities[i][d] = (w * velocities[i][d] +
                                c1 * r1 * (personal_best_positions[i][d] - particles[i][d]) +
                                c2 * r2 * (global_best_position[d] - particles[i][d]))

            particles[i][d] += velocities[i][d]
```

```
        fitness = objective_function(particles[i])

        if fitness < personal_best_scores[i]:
            personal_best_positions[i] = particles[i][:]
            personal_best_scores[i] = fitness

            if fitness < global_best_score:
                global_best_position = particles[i][:]
                global_best_score = fitness

    print(f"Iteration {iteration+1}/{max_iterations} — Best Score: {global_best_score:.5f}")

print("\nBest solution found:")
print(f"Position: {global_best_position}")
print(f"Value: {global_best_score}")
```

OUTPUT:

```
Iteration 1/10 – Best Score: 0.48527
Iteration 2/10 – Best Score: 0.07793
Iteration 3/10 – Best Score: 0.07793
Iteration 4/10 – Best Score: 0.00922
Iteration 5/10 – Best Score: 0.00922
Iteration 6/10 – Best Score: 0.00184
Iteration 7/10 – Best Score: 0.00184
Iteration 8/10 – Best Score: 0.00184
Iteration 9/10 – Best Score: 0.00184
Iteration 10/10 – Best Score: 0.00167

Best solution found:
Position: [0.03203433311405755, 0.0254515277077610 98]
Value: 0.0016739787607213353
```

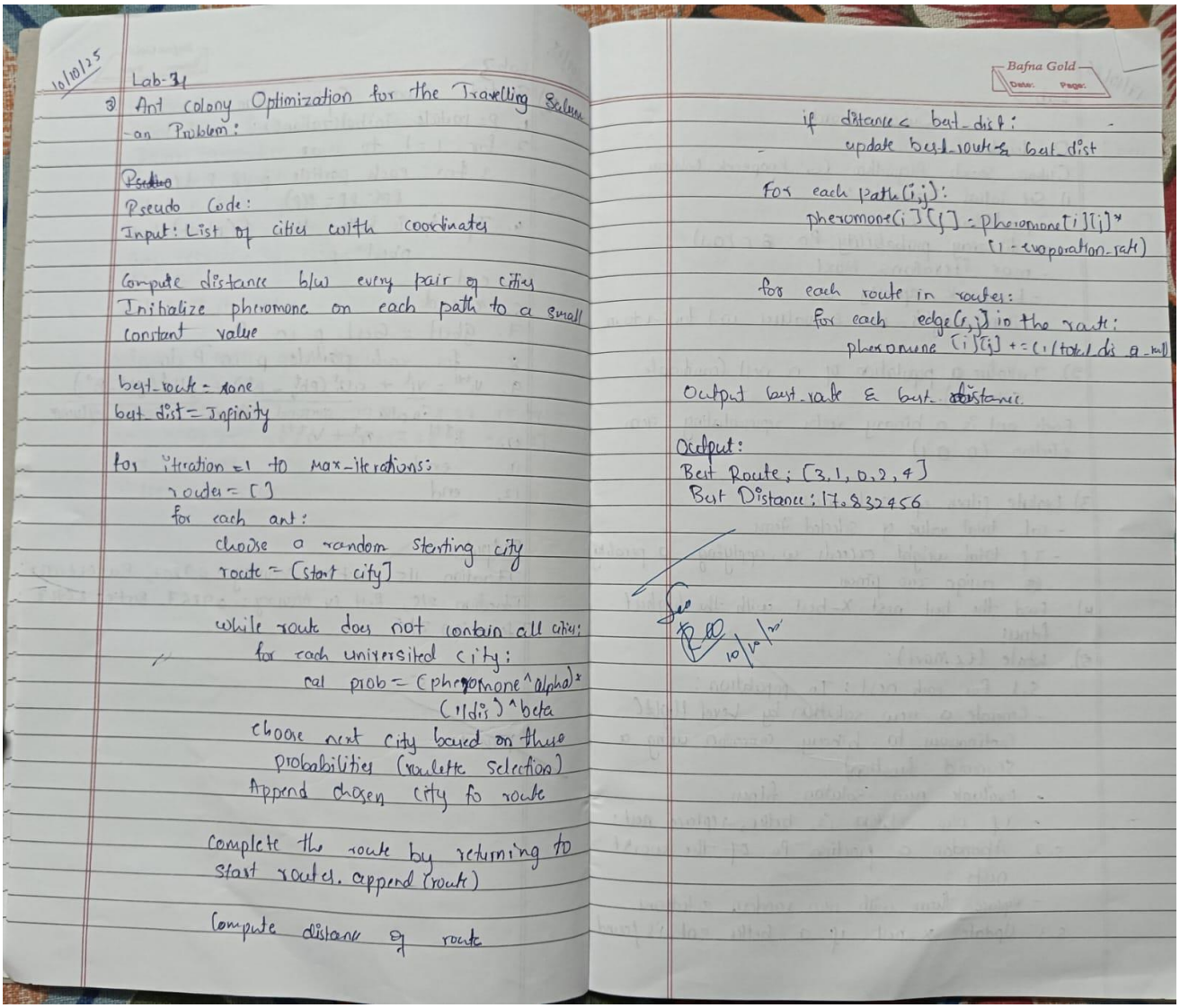
Program 3:

Ant Colony Optimization for the Traveling Salesman Problem:

The foraging behavior of ants has inspired the development of optimization algorithms that can solve complex problems such as the Traveling Salesman Problem (TSP). Ant Colony Optimization (ACO) simulates the way ants find the shortest path between food sources and their nest. Implement the ACO algorithm using Python to solve the TSP, where the objective is to find the shortest possible route that visits a list of cities and returns to the origin city.

Implementation Steps:
1. Define the Problem: Create a set of cities with their coordinates.
2. Initialize Parameters: Set the number of ants, the importance of pheromone (alpha), the importance of heuristic information (beta), the evaporation rate (rho), and the initial pheromone value.
3. Construct Solutions: Each ant constructs a solution by probabilistically choosing the next city based on pheromone trails and heuristic information.
4. Update Pheromones: After all ants have constructed their solutions, update the pheromone trails based on the quality of the solutions found.
5. Iterate: Repeat the construction and updating process for a fixed number of iterations or until convergence criteria are met.
6. Output the Best Solution: Keep track of and output the best solution found during the iterations.

Algorithm:



Code:

```
import random
import math

class ACO_TSP:
    def __init__(self, distances, n_ants=10, n_iterations=100, alpha=1, beta=5, rho=0.5, Q=100):
        self.distances = distances
        self.n = len(distances)
        self.n_ants = n_ants
        self.n_iterations = n_iterations
        self.alpha = alpha
        self.beta = beta
        self.rho = rho
        self.Q = Q
```

```
    self.pheromone = [[1 for _ in range(self.n)] for _ in range(self.n)]

    self.best_length = float("inf")
    self.best_tour = None

def run(self):
    for it in range(self.n_iterations):
        all_tours = []
        all_lengths = []

        for ant in range(self.n_ants):
            tour = self.construct_solution()
            length = self.compute_length(tour)

            all_tours.append(tour)
            all_lengths.append(length)

            if length < self.best_length:
                self.best_length = length
                self.best_tour = tour

        self.update_pheromones(all_tours, all_lengths)

    return self.best_tour, self.best_length

def construct_solution(self):
    start = random.randint(0, self.n - 1)
    tour = [start]
    unvisited = set(range(self.n))
    unvisited.remove(start)

    current = start
    while unvisited:
        next_city = self.choose_next_city(current, unvisited)
        tour.append(next_city)
        unvisited.remove(next_city)
        current = next_city

    return tour

def choose_next_city(self, current, unvisited):
    probs = []
    total = 0
    for city in unvisited:
        tau = self.pheromone[current][city] ** self.alpha
        eta = (1.0 / self.distances[current][city]) ** self.beta
        value = tau * eta
```

```
            probs.append((city, value))
            total += value

        r = random.random() * total
        cumulative = 0
        for city, value in probs:
            cumulative += value
            if cumulative >= r:
                return city
        return probs[-1][0]

    def compute_length(self, tour):
        length = 0
        for i in range(len(tour) - 1):
            length += self.distances[tour[i]][tour[i+1]]
        length += self.distances[tour[-1]][tour[0]]
        return length

    def update_pheromones(self, all_tours, all_lengths):
        for i in range(self.n):
            for j in range(self.n):
                self.pheromone[i][j] *= (1 - self.rho)

        for tour, length in zip(all_tours, all_lengths):
            for i in range(len(tour) - 1):
                a, b = tour[i], tour[i+1]
                self.pheromone[a][b] += self.Q / length
                self.pheromone[b][a] += self.Q / length
            a, b = tour[-1], tour[0]
            self.pheromone[a][b] += self.Q / length
            self.pheromone[b][a] += self.Q / length

# Example usage
if __name__ == "__main__":
    distances = [
        [0, 2, 9, 10, 7],
        [1, 0, 6, 4, 3],
        [15, 7, 0, 8, 3],
        [6, 3, 12, 0, 11],
        [9, 7, 5, 6, 0]
    ]

    aco = ACO_TSP(distances, n_ants=10, n_iterations=50, alpha=1, beta=5, rho=0.5, Q=100)
    best_tour, best_length = aco.run()

    # Format tour as edges
    path_str = " -> ".join(map(str, best_tour)) + f" -> {best_tour[0]}"
```

```
print("\n=== Final Best Solution ===")
print("Best path:", path_str)
print("Best path length:", best_length)
```

OUTPUT:

```
=== Final Best Solution ===
Best path: 2 -> 4 -> 3 -> 1 -> 0 -> 2
Best path length: 22
```

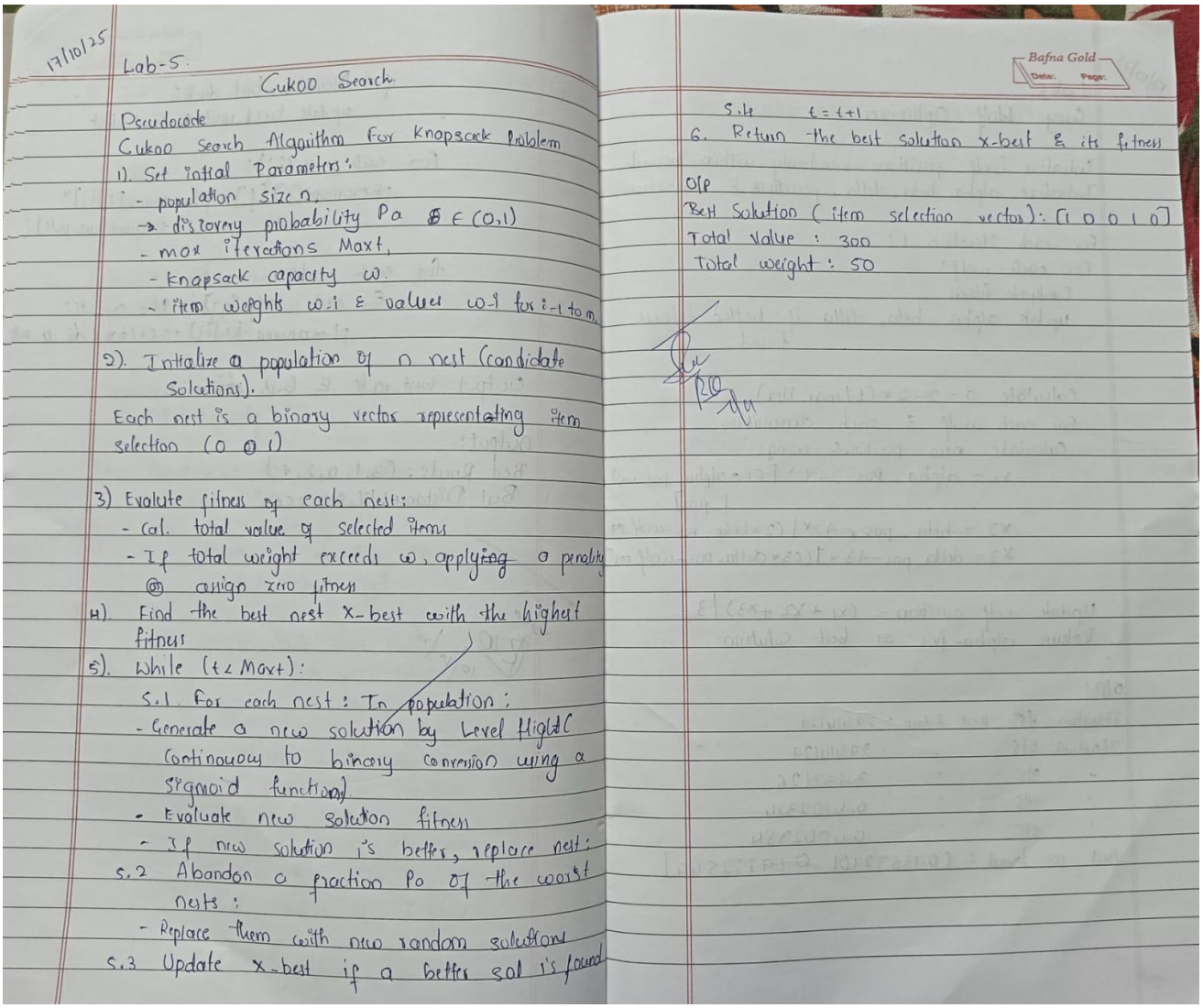
Program 4:

Cuckoo Search (CS):

Cuckoo Search (CS) is a nature-inspired optimization algorithm based on the brood parasitism of some cuckoo species. This behavior involves laying eggs in the nests of other birds, leading to the optimization of survival strategies. CS uses Lévy flights to generate new solutions, promoting global search capabilities and avoiding local minima. The algorithm is widely used for solving continuous optimization problems and has applications in various domains, including engineering design, machine learning, and data mining.

Implementation Steps:
1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the number of nests, the probability of discovery, and the number of iterations.
3. Initialize Population: Generate an initial population of nests with random positions.
4. Evaluate Fitness: Evaluate the fitness of each nest based on the optimization function.
5. Generate New Solutions: Create new solutions via Lévy flights.
6. Abandon Worst Nests: Abandon a fraction of the worst nests and replace them with new random positions.
7. Iterate: Repeat the evaluation, updating, and replacement process for a fixed number of iterations or until convergence criteria are met.
8. Output the Best Solution: Track and output the best solution found during the iterations.

Algorithm:



Code:

```
import numpy as np

# Problem data (same as before)
weights = np.array([12, 7, 11, 8, 9])
values = np.array([24, 13, 23, 15, 16])
capacity = 26

n = 10       # Number of nests
Pa = 0.25    # Probability of abandoning worst nests
max_iter = 100

def fitness(solution):
    total_weight = np.sum(solution * weights)
    if total_weight > capacity:
        return 0
```

```
    else:
        return np.sum(solution * values)

def initial_nests(n, dim):
    return np.random.randint(0, 2, (n, dim))

def levy_flight(Lambda=1.5):
    sigma = (np.math.gamma(1 + Lambda) * np.sin(np.pi * Lambda / 2) /
             (np.math.gamma((1 + Lambda) / 2) * Lambda * 2 ** ((Lambda - 1) / 2))) ** (1 /
Lambda)
    u = np.random.normal(0, sigma, size=weights.shape[0])
    v = np.random.normal(0, 1, size=weights.shape[0])
    step = u / np.abs(v) ** (1 / Lambda)
    return step

def get_new_solution(nest):
    step_size = levy_flight()
    new_sol_cont = nest + 0.01 * step_size * (nest - np.mean(nest))
    s = 1 / (1 + np.exp(-new_sol_cont))
    new_sol = np.array([1 if x > 0.5 else 0 for x in s])
    return new_sol

def abandon_worst_nests(nests, fitnesses, Pa):
    num_abandon = int(Pa * len(nests))
    worst_indices = np.argsort(fitnesses)[:num_abandon]
    for i in worst_indices:
        nests[i] = np.random.randint(0, 2, nests.shape[1])
        fitnesses[i] = fitness(nests[i])
    return nests, fitnesses

def cuckoo_search():
    dim = weights.shape[0]
    t = 0

    # Step 4 and 5: Initialize population and evaluate fitness
    nests = initial_nests(n, dim)
    fitnesses = np.array([fitness(nest) for nest in nests])

    while t < max_iter:
        for i in range(n):
            # Step 7 and 8: Generate cuckoo and evaluate fitness
            cuckoo = get_new_solution(nests[i])
            cuckoo_fit = fitness(cuckoo)

            # Step 9: Choose a nest randomly
            j = np.random.randint(n)
```

```
            # Step 10-12: Replace if cuckoo is better
            if cuckoo_fit > fitnesses[j]:
                nests[j] = cuckoo
                fitnesses[j] = cuckoo_fit

        # Step 13 and 14: Abandon fraction Pa of worst nests and build new ones
        nests, fitnesses = abandon_worst_nests(nests, fitnesses, Pa)

        # Step 15 and 16: Keep and rank the best solution
        best_index = np.argmax(fitnesses)
        best_nest = nests[best_index].copy()
        best_fitness = fitnesses[best_index]

        print(f"Iteration {t+1}: Best fitness = {best_fitness}")

        t += 1

    # Step 19: Output the best solution
    return best_nest, best_fitness

best_solution, best_val = cuckoo_search()

print("\nBest solution found:")
print("Items selected:", best_solution)
print("Total value:", best_val)
print("Total weight:", np.sum(best_solution * weights))
```

OUTPUT:

```
Best solution found: [1 0 0 1 0]
Total value: 50
Total weight: 25
```

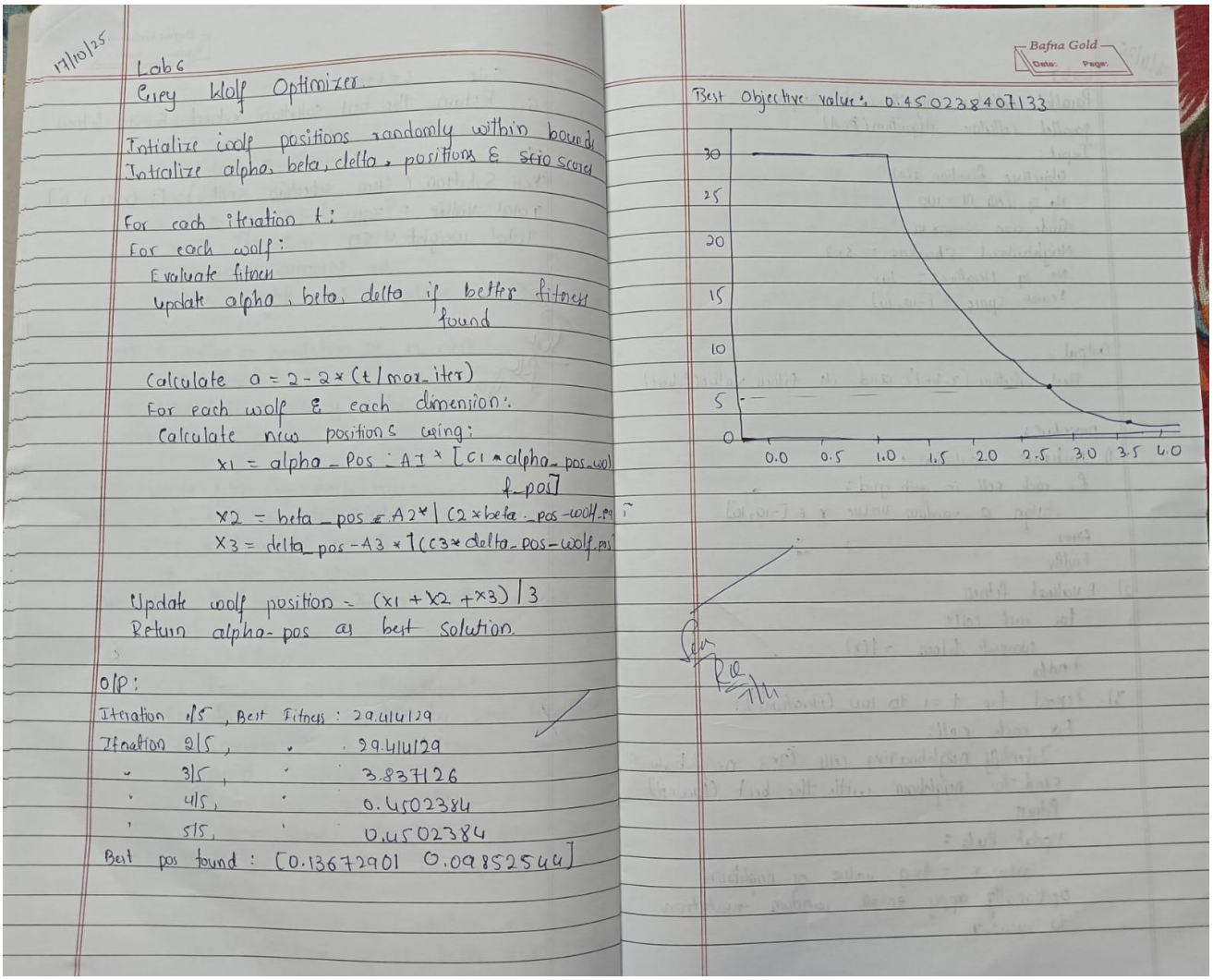
Program 5:

Grey Wolf Optimizer (GWO):

The Grey Wolf Optimizer (GWO) algorithm is a swarm intelligence algorithm inspired by the social hierarchy and hunting behavior of grey wolves. It mimics the leadership structure of alpha, beta, delta, and omega wolves and their collaborative hunting strategies. The GWO algorithm uses these social hierarchies to model the optimization process, where the alpha wolves guide the search process while beta and delta wolves assist in refining the search direction. This algorithm is effective for continuous optimization problems and has applications in engineering, data analysis, and machine learning.

Implementation Steps:
1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the number of wolves and the number of iterations.
3. Initialize Population: Generate an initial population of wolves with random positions.
4. Evaluate Fitness: Evaluate the fitness of each wolf based on the optimization function.
5. Update Positions: Update the positions of the wolves based on the positions of alpha, beta, and delta wolves.
6. Iterate: Repeat the evaluation and position updating process for a fixed number of iterations or until convergence criteria are met.
7. Output the Best Solution: Track and output the best solution found during the iterations

Algorithm:



Code:

```
import numpy as np
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier

# Load dataset
data = load_breast_cancer()
X = data.data
y = data.target
num_features = X.shape[1]

# Gray Wolf Optimizer parameters
num_wolves = 10  # Population size
max_iter = 10    # Number of iterations

# Binary GWO helper functions
```

```
def sigmoid(x):
    return 1 / (1 + np.exp(-x))

def binary_transform(x):
    return np.where(sigmoid(x) > np.random.rand(len(x)), 1, 0)

# Fitness function: classification accuracy
def fitness(position):
    selected_features = np.where(position == 1)[0]
    if len(selected_features) == 0:
        return 0
    X_selected = X[:, selected_features]
    clf = RandomForestClassifier(n_estimators=50)
    score = cross_val_score(clf, X_selected, y, cv=5).mean()
    return score

# Initialize wolves
wolves = np.random.uniform(-1, 1, (num_wolves, num_features))
binary_wolves = np.array([binary_transform(w) for w in wolves])
fitness_vals = np.array([fitness(w) for w in binary_wolves])

# Initialize alpha, beta, delta
alpha_idx = np.argmax(fitness_vals)
alpha = wolves[alpha_idx].copy()
alpha_score = fitness_vals[alpha_idx]

beta_idx = np.argsort(fitness_vals)[-2]
beta = wolves[beta_idx].copy()
beta_score = fitness_vals[beta_idx]

delta_idx = np.argsort(fitness_vals)[-3]
delta = wolves[delta_idx].copy()
delta_score = fitness_vals[delta_idx]

# Main loop
for t in range(max_iter):
    a = 2 - t * (2 / max_iter)  # Linearly decreasing a

    for i in range(num_wolves):
        for j in range(num_features):
            r1, r2 = np.random.rand(), np.random.rand()
            A1 = 2 * a * r1 - a
            C1 = 2 * r2
            D_alpha = abs(C1 * alpha[j] - wolves[i][j])
            X1 = alpha[j] - A1 * D_alpha

            r1, r2 = np.random.rand(), np.random.rand()
```

```
            A2 = 2 * a * r1 - a
            C2 = 2 * r2
            D_beta = abs(C2 * beta[j] - wolves[i][j])
            X2 = beta[j] - A2 * D_beta

            r1, r2 = np.random.rand(), np.random.rand()
            A3 = 2 * a * r1 - a
            C3 = 2 * r2
            D_delta = abs(C3 * delta[j] - wolves[i][j])
            X3 = delta[j] - A3 * D_delta

            wolves[i][j] = (X1 + X2 + X3) / 3

    # Update binary positions
    binary_wolves = np.array([binary_transform(w) for w in wolves])
    fitness_vals = np.array([fitness(w) for w in binary_wolves])

    # Update alpha, beta, delta
    sorted_idx = np.argsort(fitness_vals)[::-1]
    alpha, alpha_score = wolves[sorted_idx[0]].copy(), fitness_vals[sorted_idx[0]]
    beta, beta_score = wolves[sorted_idx[1]].copy(), fitness_vals[sorted_idx[1]]
    delta, delta_score = wolves[sorted_idx[2]].copy(), fitness_vals[sorted_idx[2]]

    print(f"Iteration {t+1}/{max_iter}, Best fitness: {alpha_score:.4f}")

# Best feature subset
best_features = np.where(binary_transform(alpha) == 1)[0]
print("Selected feature indices:", best_features)
print("Number of features selected:", len(best_features))
```

OUTPUT:

```
Iteration 1/10, Best fitness: 0.9667
Iteration 2/10, Best fitness: 0.9666
Iteration 3/10, Best fitness: 0.9614
Iteration 4/10, Best fitness: 0.9631
Iteration 5/10, Best fitness: 0.9666
Iteration 6/10, Best fitness: 0.9719
Iteration 7/10, Best fitness: 0.9649
Iteration 8/10, Best fitness: 0.9614
Iteration 9/10, Best fitness: 0.9649
Iteration 10/10, Best fitness: 0.9719
Selected feature indices: [ 0  3  4  6  9 16 18 20 22 23 25 27 28 29]
Number of features selected: 14
```

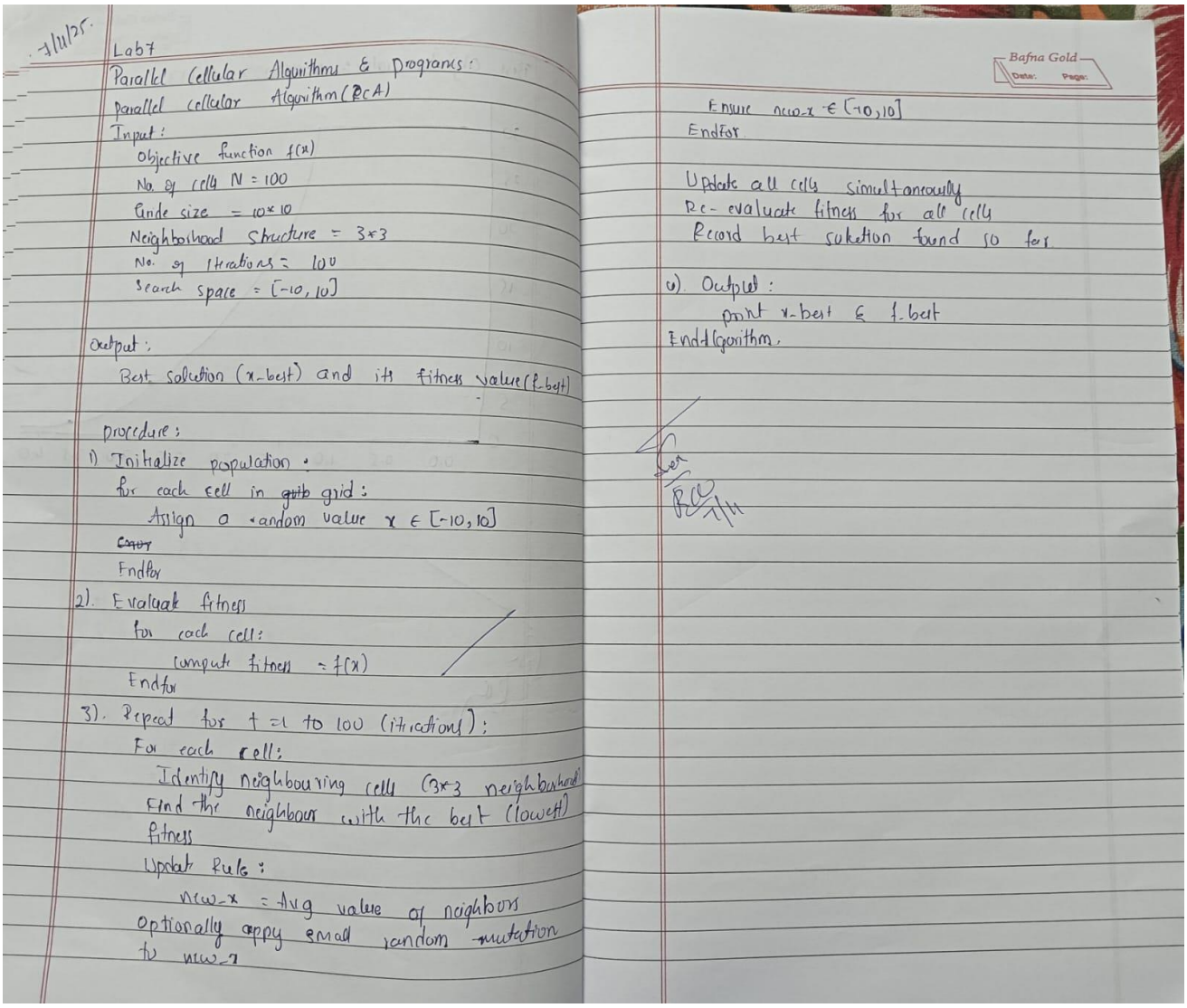
Program 6:

Parallel Cellular Algorithms and Programs:

Parallel Cellular Algorithms are inspired by the functioning of biological cells that operate in a highly parallel and distributed manner. These algorithms leverage the principles of cellular automata and parallel computing to solve complex optimization problems efficiently. Each cell represents a potential solution and interacts with its neighbors to update its state based on predefined rules. This interaction models the diffusion of information across the cellular grid, enabling the algorithm to explore the search space effectively. Parallel Cellular Algorithms are particularly suitable for large-scale optimization problems and can be implemented on parallel computing architectures for enhanced performance.

Implementation Steps:
1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the number of cells, grid size, neighborhood structure, and number of iterations. 3. Initialize Population: Generate an initial population of cells with random positions in the solution space.
4. Evaluate Fitness: Evaluate the fitness of each cell based on the optimization function.
5. Update States: Update the state of each cell based on the states of its neighboring cells and predefined update rules.
6. Iterate: Repeat the evaluation and state updating process for a fixed number of iterations or until convergence criteria are met.
7. Output the Best Solution: Track and output the best solution found during the iterations.

Algorithm:



Code:

```
import numpy as np
import matplotlib.pyplot as plt
from skimage import data, util

def get_neighbors_indices(row, col, max_row, max_col):
    neighbors = []
    for dr in [-1, 0, 1]:
        for dc in [-1, 0, 1]:
            if dr == 0 and dc == 0:
                continue
            nr, nc = row + dr, col + dc
            if 0 <= nr < max_row and 0 <= nc < max_col:
                neighbors.append((nr, nc))
    return neighbors
```

```
def pca_noise_reduction(image, max_iterations=10, sigma=15):
    rows, cols = image.shape
    denoised_image = image.copy().astype(float)

    for iteration in range(max_iterations):
        new_image = denoised_image.copy()

        for i in range(rows):
            for j in range(cols):
                neighbors = get_neighbors_indices(i, j, rows, cols)

                weights = []
                intensities = []

                for nr, nc in neighbors:
                    diff = abs(denoised_image[nr, nc] - denoised_image[i, j])
                    weight = np.exp(-diff / sigma)
                    weights.append(weight)
                    intensities.append(denoised_image[nr, nc])

                weights = np.array(weights)
                intensities = np.array(intensities)

                if weights.sum() > 0:
                    new_value = np.sum(weights * intensities) / np.sum(weights)
                    new_image[i, j] = new_value

        denoised_image = new_image

    return denoised_image.astype(np.uint8)

# Load sample grayscale image: "camera"
image = data.camera()  # shape: (512, 512)

# Add salt & pepper noise
noisy_image = util.random_noise(image, mode='s&p', amount=0.05)
noisy_image = (noisy_image * 255).astype(np.uint8)

# Apply PCA-based denoising
denoised = pca_noise_reduction(noisy_image, max_iterations=10, sigma=20)

# 📌 Print only the 5×5 pixel values for comparison
print("\nOriginal Image 5x5 patch:")
print(image[100:105, 100:105])

print("\nNoisy Image 5x5 patch:")
```

```
print(noisy_image[100:105, 100:105])

print("\nDenoised Image 5x5 patch:")
print(denoised[100:105, 100:105])
```

OUTPUT:

```
Original Image 5x5 patch:
[[212 212 212 213 212]
 [213 212 212 211 213]
 [213 213 213 211 212]
 [213 213 212 212 212]
 [213 212 213 212 213]]

Noisy Image 5x5 patch:
[[211 211 211 213 211]
 [  0 211 211 211 213]
 [213 213 213 211 211]
 [213 213 211 211 211]
 [213 211 255 211 213]]

Denoised Image 5x5 patch:
[[211 211 211 211 211]
 [211 211 211 211 211]
 [212 212 211 211 211]
 [212 212 212 211 211]
 [212 212 212 212 211]]
```

Program 7:

Optimization via Gene Expression Algorithms:

Gene Expression Algorithms (GEA) are inspired by the biological process of gene expression in living organisms. This process involves the translation of genetic information encoded in DNA into functional proteins. In GEA, solutions to optimization problems are encoded in a manner similar to genetic sequences. The algorithm evolves these solutions through selection, crossover, mutation, and gene expression to find optimal or near-optimal solutions. GEA is effective for solving complex optimization problems in various domains, including engineering, data analysis, and machine learning.

Implementation Steps:
1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the population size, number of genes, mutation rate, crossover rate, and number of generations.
3. Initialize Population: Generate an initial population of random genetic sequences.
4. Evaluate Fitness: Evaluate the fitness of each genetic sequence based on the optimization function.
5. Selection: Select genetic sequences based on their fitness for reproduction.
6. Crossover: Perform crossover between selected sequences to produce offspring.
7. Mutation: Apply mutation to the offspring to introduce variability.
8. Gene Expression: Translate genetic sequences into functional solutions.
9. Iterate: Repeat the selection, crossover, mutation, and gene expression processes for a fixed number of generations or until convergence criteria are met.
10. Output the Best Solution: Track and output the best solution found during the iterations.

Algorithm:

Lab-7

Optimization via genetic Expression Algorithm.

Step1: Fitness Function : $f(x) = x^2$

Encoding technique : 0 to 31

use chromosome of fixed length (genotype)

Step2: Initial population

S.no	(Genotype) initial chromosome	Phenotype (expression)	Value	fitness	p
1	+xx	x^2	12	144	0.1247
2	+xx	2x	25	625	0.5411
3	x	x	5	25	0.0216
4	-x2	x-2	19	361	0.3025
Sum				115	
avg				288.75	
max				625	

	actual count	expected count
	1	0.5
	2	2.0
	0	0.08
	1	1.25

Step3: Selection of mating pool

S.no	Selected chromosome	crossover point	offspring	Phenotype
1	+xx	2	+x+	$x^*(x+\ldots)$
2	+xx	1	+xx	2x
3	+xx	3	+x-	$x+(x-\ldots)$
4	-x2	1	+x2	x+2

x value	fitness
13	169
24	576
27	729
17	289

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Step4: crossover: Perform crossover randomly chosen gene position (not 1000 bits)

max fitness after crossover = 729

Step5: mutation

S.no	offspring before mutation	mutation applied	offspring after mutation	Phenotype
1	x x +	+ → -	x x -	$x^*(x-\ldots)$
2	+xx	none	+xx	2x
3	+x-	- → +	-x+	$x+x*x$
4	+x2	none	+x2	x+2

x value	fitness
29	841
24	576
27	729
20	400

Step6: Gene expression & evaluation

decode each genotype → phenotype

calculate fitness

$\Sigma f(x) = 841 + 576 + 729 + 400 = 2546$

avg = 636.5

max = 841

Step7: Iterate until convergence

Repeat step 3 to 6 until fitness improvement is negligible (or) generation limit has reached.

Pseudocode:
Define fitness function
Define parameters
Generate population
select mating pool
mutation after mating
Gene expression & evaluation
Iterate
output Best value

output : 1000 generations

Genes: [24.33, 29.82, 29.84, 28.57, 15.09,
21.83, 23.83, 30.81, 28.51, 26.22]
$x = 26.37$
$f(x) = 695.45$

Code:

```
import numpy as np
import matplotlib.pyplot as plt
from gplearn.genetic import SymbolicRegressor
from gplearn.functions import make_function
from gplearn.fitness import make_fitness

# Generate training data
X = np.linspace(-10, 10, 100).reshape(-1, 1)
y = X**2 + np.sin(X)  # True function to approximate

# Define symbolic regressor
est_gp = SymbolicRegressor(
    population_size=500,
    generations=20,
    stopping_criteria=0.01,
    p_crossover=0.7,
    p_subtree_mutation=0.1,
    p_hoist_mutation=0.05,
    p_point_mutation=0.1,
    max_samples=0.9,
    verbose=1,
    parsimony_coefficient=0.001,
    random_state=42
)

# Fit model
est_gp.fit(X, y)

# Predict on training data
y_pred = est_gp.predict(X)

# Print discovered expression
print("\nDiscovered expression:")
print(est_gp._program)

plt.figure(figsize=(10, 6))
plt.plot(X, y, label='True Function', color='blue')
plt.plot(X, y_pred, label='GEP Prediction', color='red', linestyle='--')
plt.legend()
plt.title("Gene Expression Programming (Symbolic Regression)")
plt.xlabel("X")
plt.ylabel("y")
plt.grid(True)
plt.show()
```

OUTPUT:

```
Predicted values (first 10):
[-99.99 -96.61 -93.23 -89.85 -86.47 -83.09 -79.7  -76.32 -72.94 -69.56]
```