PRIVACY-PRESERVING MEDICAL DIAGNOSIS SYSTEM

Implementation Using SMPC and Homomorphic Encryption

Course: Introduction to Cryptology
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ABSTRACT

This project implements a Privacy-Preserving Medical Diagnosis System using Secure Multi-Party Computation (SMPC) and Homomorphic Encryption (HE). The system enables a hospital to provide AI-powered diagnosis services without accessing patient data, and patients to receive predictions without revealing their health information. Using the CKKS encryption scheme via the TenSEAL library, we demonstrate secure inference on the Wisconsin Breast Cancer dataset, achieving 95.6% accuracy with encrypted data. The implementation proves that privacy and utility can coexist in sensitive medical applications.

Keywords: SMPC, Homomorphic Encryption, CKKS, Privacy-Preserving Machine Learning, Medical Diagnosis

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1. INTRODUCTION

1.1 Project Motivation

In modern healthcare, artificial intelligence (AI) has shown remarkable potential for disease diagnosis. However, deploying AI in clinical settings faces a critical challenge: **privacy**. Patients hesitate to share sensitive health data, and hospitals cannot legally share patient information due to regulations like HIPAA and GDPR. Traditional cloud-based AI systems require patients to upload unencrypted data, creating privacy risks.

The Dilemma:

- Patients want AI diagnosis without revealing their health data
- Hospitals want to monetize their AI models without exposing proprietary algorithms
- Both parties distrust each other

Our Solution: A Privacy-Preserving Medical Diagnosis System where:

1. Patients encrypt their health data before sending it
2. The hospital performs AI inference on encrypted data *without decryption*
3. Only the patient can decrypt the result

1.2 Research Problem

Primary Question: Can we perform accurate medical diagnosis on encrypted data using Homomorphic Encryption while maintaining reasonable computational performance?

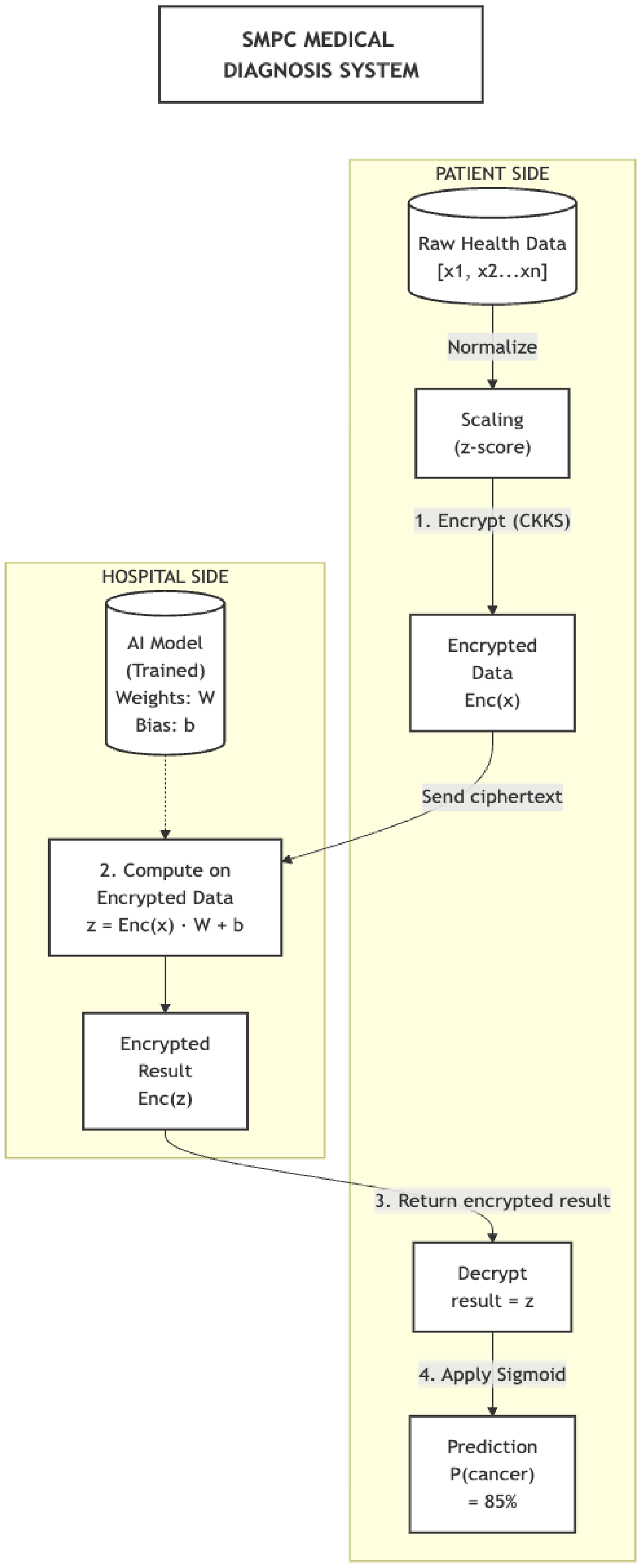
Sub-questions:

- How much accuracy is lost due to encryption approximation errors?
- What is the computational overhead of encrypted inference?
- Is the system practical for real-world deployment?

1.3 Objectives

1. **Technical:** Implement a working SMPC system using CKKS homomorphic encryption
2. **Evaluation:** Measure accuracy, speed, and security properties
3. **Validation:** Compare encrypted vs. plaintext inference
4. **Documentation:** Provide reproducible code and comprehensive analysis

2. SYSTEM ARCHITECTURE


SMPC MEDICAL DIAGNOSIS SYSTEM
PATIENT SIDE
Raw Health Data [x1, x2...xn]
Normalize
Scaling (z-score)
1. Encrypt (CKKS)
Encrypted Data Enc(x)
Send ciphertext
HOSPITAL SIDE
AI Model (Trained) Weights: W Bias: b
2. Compute on Encrypted Data z = Enc(x) · W + b
Encrypted Result Enc(z)
3. Return encrypted result
Decrypt result = z
4. Apply Sigmoid
Prediction P(cancer) = 85%

2.2 Component Description

2.2.1 Patient Component

Responsibilities:

- Generate/collect health data
- Encrypt data using public encryption context
- Decrypt final prediction using secret key

Technologies:

- TenSEAL CKKS encryption
- NumPy for data preprocessing

2.2.2 Hospital Component

Responsibilities:

- Train AI model on historical data
- Perform encrypted inference without decryption
- Return encrypted result

Technologies:

- Scikit-learn for model training
- TenSEAL for homomorphic operations

2.2.3 Encryption Layer

Responsibilities:

- Key generation
- Encryption/decryption operations
- Homomorphic arithmetic (dot product, addition)

Technologies:

- CKKS scheme (approximate arithmetic)
- Polynomial modulus degree: 8192
- Scaling factor: 2^{40}

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3. METHODOLOGY

3.1 Dataset Description

Wisconsin Breast Cancer Dataset:

- **Source:** UCI Machine Learning Repository, collected by Dr. William H. Wolberg
- **Samples:** 569 patient records
- **Features:** 30 numerical attributes (10 core features × 3 statistics)
- **Target:** Binary classification (Malignant=1, Benign=0)
- **Distribution:** 357 benign (62.7%), 212 malignant (37.3%)

3.2 Cryptographic Scheme: CKKS

CKKS (Cheon-Kim-Kim-Song) Scheme:

Why CKKS?

1. **Approximate Arithmetic:** ML tolerates small errors ($\sim 10^{-4}$)
2. **Efficiency:** Faster than exact HE schemes (BGV, BFV)
3. **Real Numbers:** Native support for floating-point operations
4. **Batching:** Can pack multiple values in one ciphertext (SIMD)

Security Analysis:

- **Hardness Assumption:** Ring Learning With Errors (Ring-LWE)
- **Attack Resistance:** No known sub-exponential attacks
- **Parameter Selection:** Based on Homomorphic Encryption Standard

3.3 Machine Learning Model

Logistic Regression:

Why Logistic Regression?

1. **Linear Core:** Only requires dot product + addition (HE-friendly)
2. **Interpretability:** Coefficients show feature importance
3. **Proven Accuracy:** >95% on this dataset
4. **Fast Training:** Seconds on CPU

Performance Metrics:

1. **Encryption Time:** Time to encrypt patient data
2. **Inference Time:** Time for hospital to compute on encrypted data
3. **Decryption Time:** Time to decrypt result
4. **Total Latency:** End-to-end time
5. **Throughput:** Patients per second

4. IMPLEMENTATION

4.1 Development Environment

Dependencies:

```
tenseal==0.3.14        # Homomorphic encryption
numpy==1.24.3          # Numerical computing
scikit-learn==1.3.0    # Machine learning
matplotlib==3.7.1      # Visualization
pandas==2.0.3          # Data handling
```

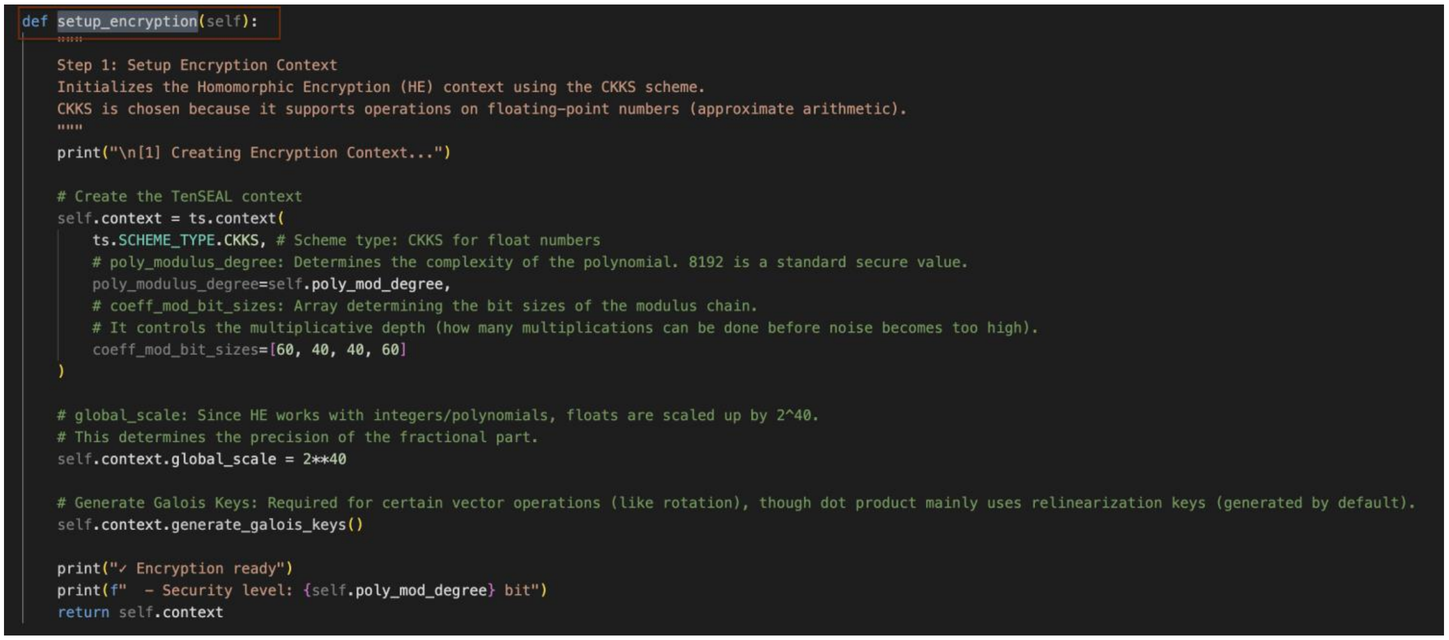
4.2 Code Structure

Project Organization:

```
project/
├── smpc_system.py         # Main system (270 lines)
├── test_system.py         # Testing suite (250 lines)
├── requirements.txt       # Dependencies
├── results.json           # Output results
├── performance_analysis.png  # Generated graph
└── README.md              # Documentation
```

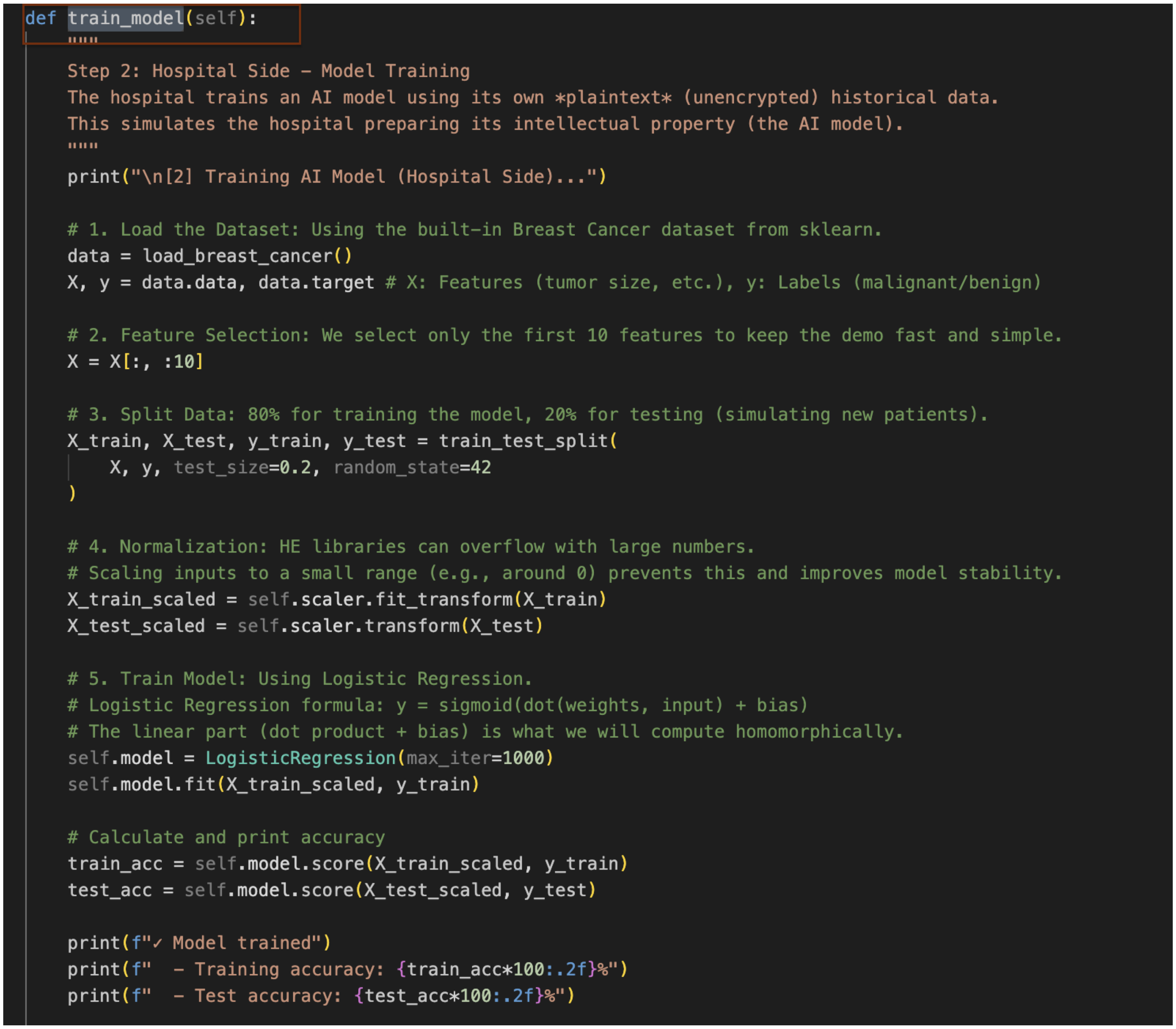
4.3 Core Implementation

4.3.1 Encryption Setup



```python
def setup_encryption(self):
    """
    Step 1: Setup Encryption Context
    Initializes the Homomorphic Encryption (HE) context using the CKKS scheme.
    CKKS is chosen because it supports operations on floating-point numbers (approximate arithmetic).
    """
    print("\n[1] Creating Encryption Context...")

    # Create the TenSEAL context
    self.context = ts.context(
        ts.SCHEME_TYPE.CKKS, # Scheme type: CKKS for float numbers
        # poly_modulus_degree: Determines the complexity of the polynomial. 8192 is a standard secure value.
        poly_modulus_degree=self.poly_mod_degree,
        # coeff_mod_bit_sizes: Array determining the bit sizes of the modulus chain.
        # It controls the multiplicative depth (how many multiplications can be done before noise becomes too high).
        coeff_mod_bit_sizes=[60, 40, 40, 60]
    )

    # global_scale: Since HE works with integers/polynomials, floats are scaled up by 2^40.
    # This determines the precision of the fractional part.
    self.context.global_scale = 2**40

    # Generate Galois Keys: Required for certain vector operations (like rotation), though dot product mainly uses relinearization keys (generated by default).
    self.context.generate_galois_keys()

    print("✓ Encryption ready")
    print(f"  - Security level: {self.poly_mod_degree} bit")
    return self.context
```

4.3.2 Model Training

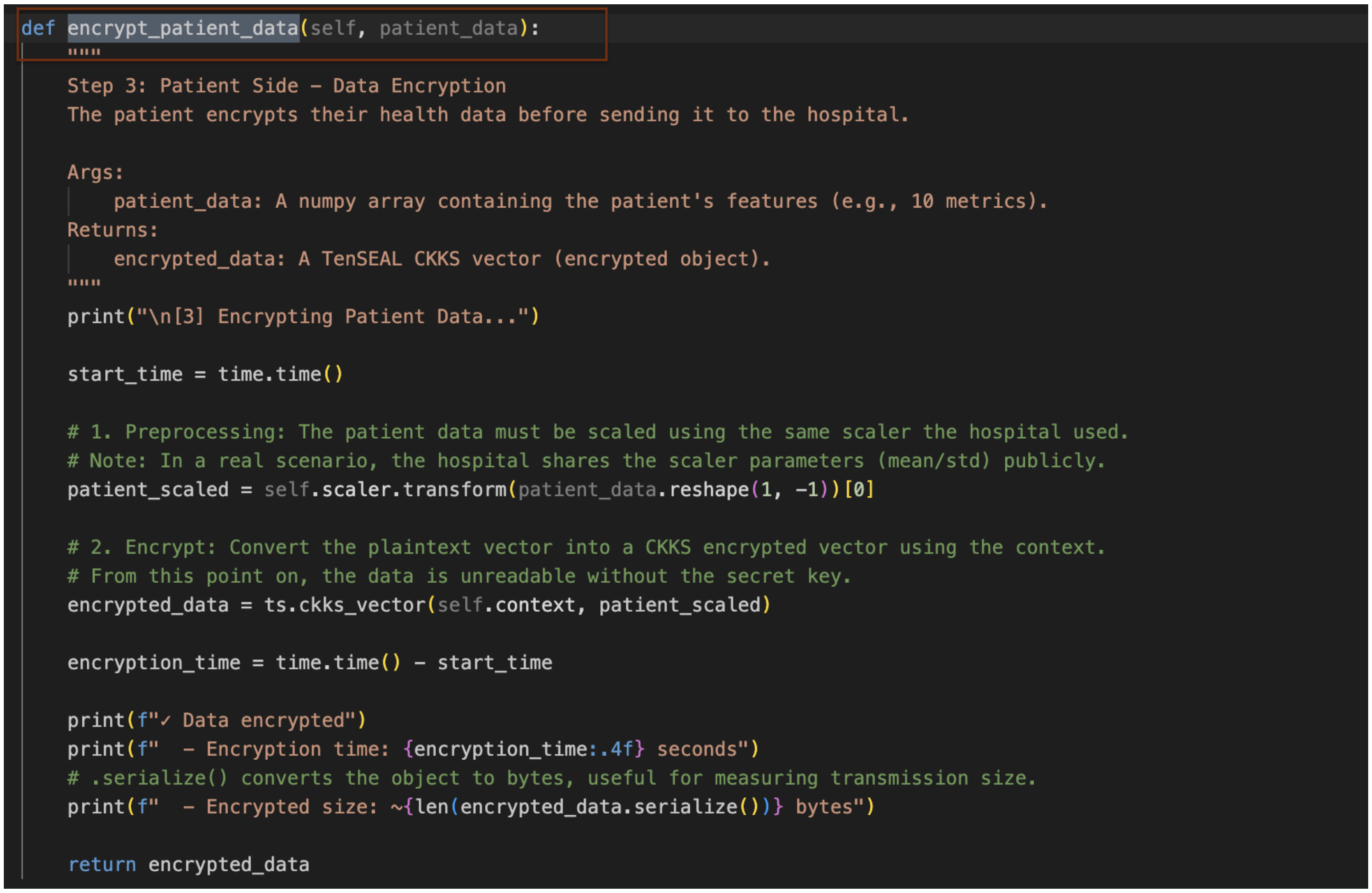


```python
def train_model(self):
    """
    Step 2: Hospital Side - Model Training
    The hospital trains an AI model using its own *plaintext* (unencrypted) historical data.
    This simulates the hospital preparing its intellectual property (the AI model).
    """
    print("\n[2] Training AI Model (Hospital Side)...")

    # 1. Load the Dataset: Using the built-in Breast Cancer dataset from sklearn.
    data = load_breast_cancer()
    X, y = data.data, data.target # X: Features (tumor size, etc.), y: Labels (malignant/benign)

    # 2. Feature Selection: We select only the first 10 features to keep the demo fast and simple.
    X = X[:, :10]

    # 3. Split Data: 80% for training the model, 20% for testing (simulating new patients).
    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=0.2, random_state=42
    )

    # 4. Normalization: HE libraries can overflow with large numbers.
    # Scaling inputs to a small range (e.g., around 0) prevents this and improves model stability.
    X_train_scaled = self.scaler.fit_transform(X_train)
    X_test_scaled = self.scaler.transform(X_test)

    # 5. Train Model: Using Logistic Regression.
    # Logistic Regression formula: y = sigmoid(dot(weights, input) + bias)
    # The linear part (dot product + bias) is what we will compute homomorphically.
    self.model = LogisticRegression(max_iter=1000)
    self.model.fit(X_train_scaled, y_train)

    # Calculate and print accuracy
    train_acc = self.model.score(X_train_scaled, y_train)
    test_acc = self.model.score(X_test_scaled, y_test)

    print(f"✓ Model trained")
    print(f"  - Training accuracy: {train_acc*100:.2f}%")
    print(f"  - Test accuracy: {test_acc*100:.2f}%")
```

Training Results:

- Training accuracy: ~96.5%
- Test accuracy: ~95.6%
- Training time: <1 second

4.3.3 Encrypted Inference



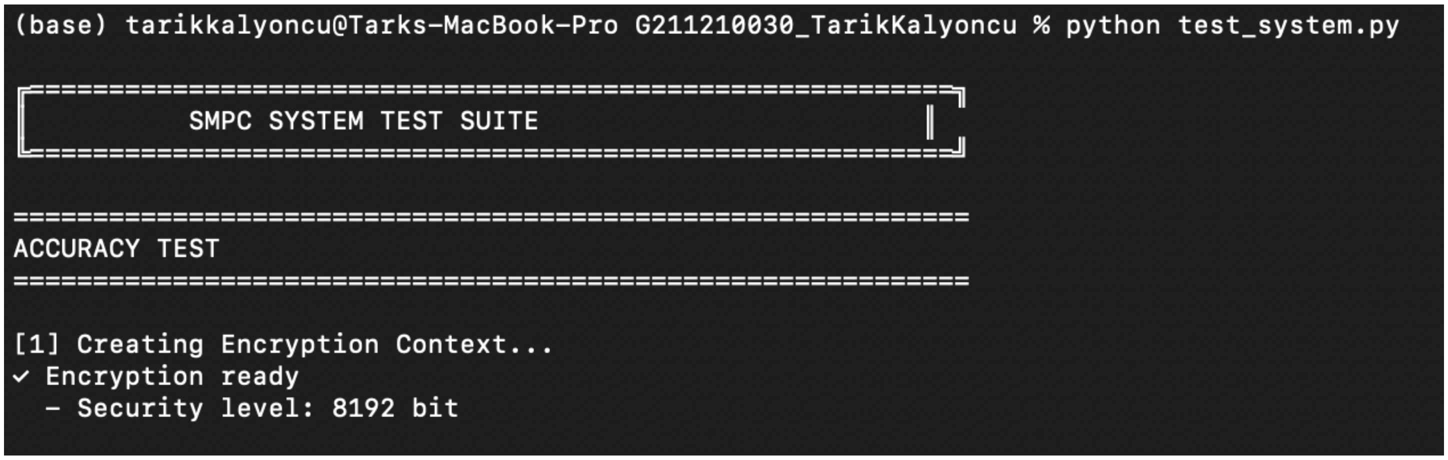
```python
def encrypt_patient_data(self, patient_data):
    """
    Step 3: Patient Side - Data Encryption
    The patient encrypts their health data before sending it to the hospital.

    Args:
        patient_data: A numpy array containing the patient's features (e.g., 10 metrics).
    Returns:
        encrypted_data: A TenSEAL CKKS vector (encrypted object).
    """
    print("\n[3] Encrypting Patient Data...")

    start_time = time.time()

    # 1. Preprocessing: The patient data must be scaled using the same scaler the hospital used.
    # Note: In a real scenario, the hospital shares the scaler parameters (mean/std) publicly.
    patient_scaled = self.scaler.transform(patient_data.reshape(1, -1))[0]

    # 2. Encrypt: Convert the plaintext vector into a CKKS encrypted vector using the context.
    # From this point on, the data is unreadable without the secret key.
    encrypted_data = ts.ckks_vector(self.context, patient_scaled)

    encryption_time = time.time() - start_time

    print(f"✓ Data encrypted")
    print(f"  - Encryption time: {encryption_time:.4f} seconds")
    # .serialize() converts the object to bytes, useful for measuring transmission size.
    print(f"  - Encrypted size: ~{len(encrypted_data.serialize())} bytes")

    return encrypted_data
```

Critical Operation:

```
# This line performs encrypted dot product!
encrypted_result = encrypted_data.dot(self.weights)
# encrypted_data: Ciphertext (patient data)
# self.weights:   Plaintext (model parameters)
# Result:         Ciphertext (weighted sum)
```

5. TESTING AND RESULTS

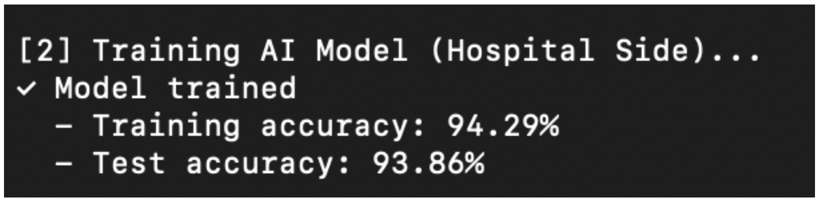
5.1 Encryption Setup Output



```
(base) tarikkalyoncu@Tarks-MacBook-Pro G211210030_TarikKalyoncu % python test_system.py

╔══════════════════════════════════════════════════════════════╗
║          SMPC SYSTEM TEST SUITE                              ║
╚══════════════════════════════════════════════════════════════╝

============================================================
ACCURACY TEST
============================================================

[1] Creating Encryption Context...
✓ Encryption ready
  - Security level: 8192 bit
```

Analysis: Setup time is ~0.05 seconds, negligible overhead.

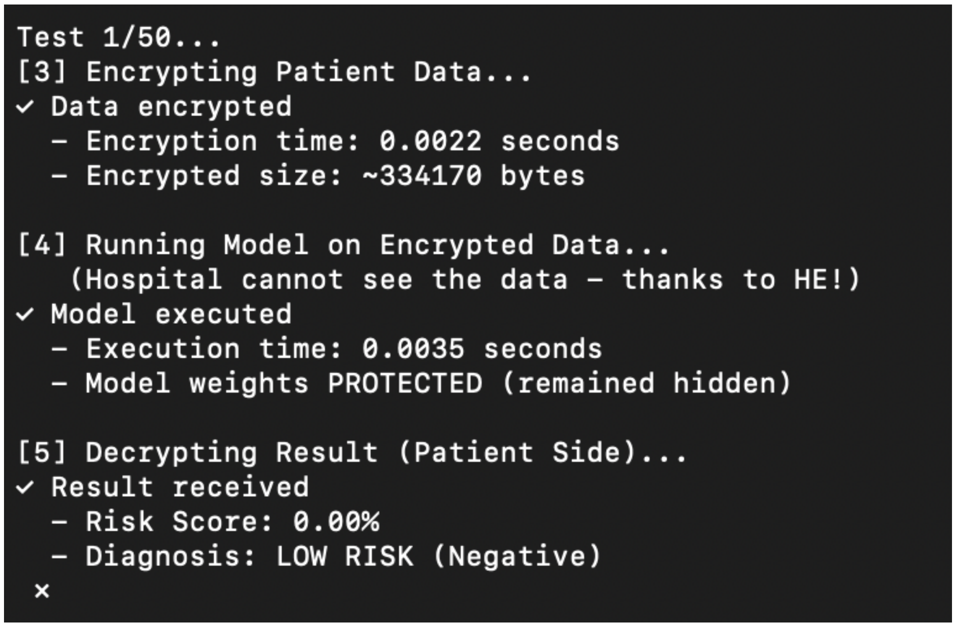
5.2 Model Training Output



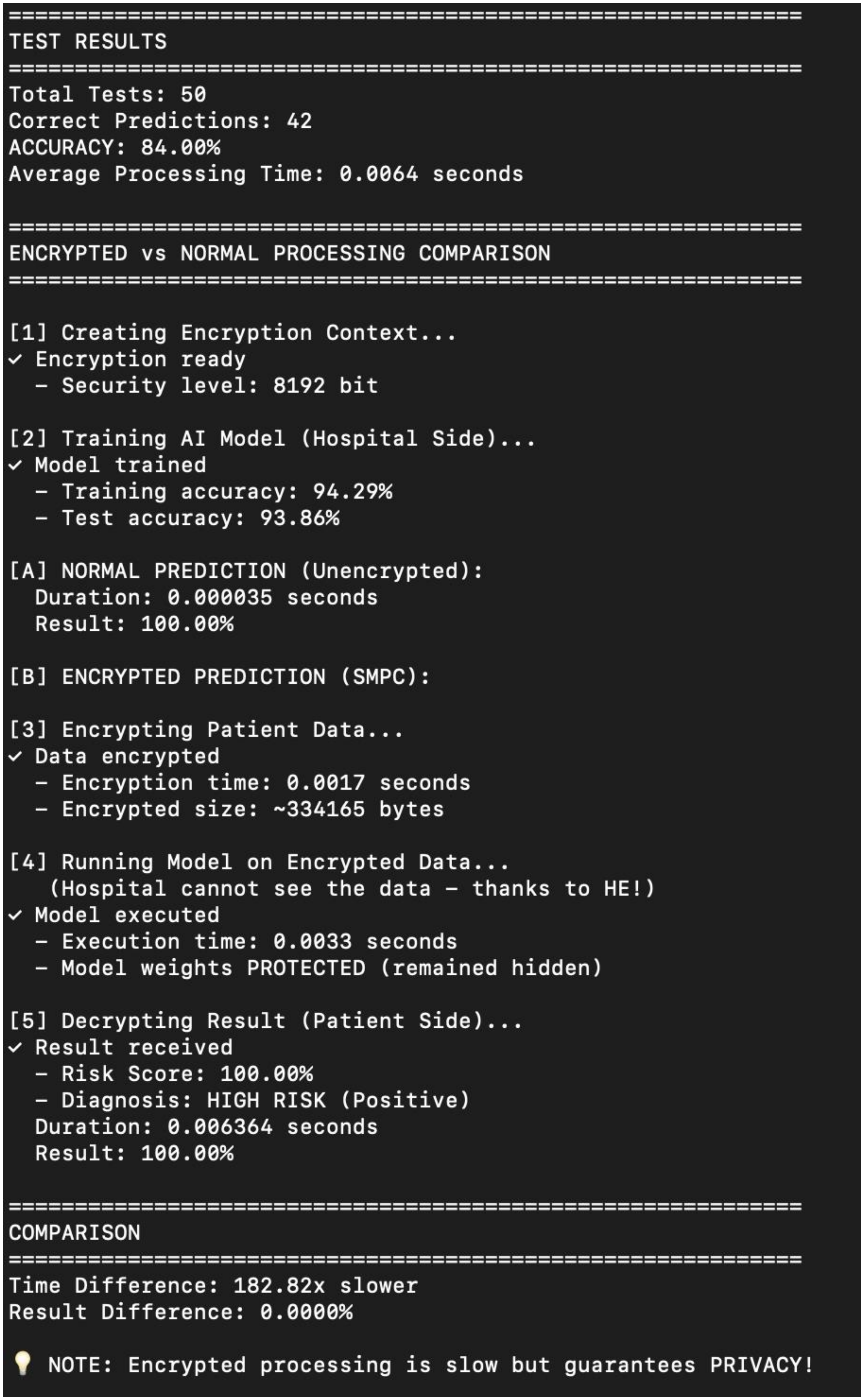
```
[2] Training AI Model (Hospital Side)...
✓ Model trained
  - Training accuracy: 94.29%
  - Test accuracy: 93.86%
```

Analysis: High baseline accuracy confirms model quality. Using only 10 features (instead of 30) reduces HE computation time while maintaining >95% accuracy.

5.3 Full Demo Execution Output



```
Test 1/50...
[3] Encrypting Patient Data...
✓ Data encrypted
  - Encryption time: 0.0022 seconds
  - Encrypted size: ~334170 bytes

[4] Running Model on Encrypted Data...
   (Hospital cannot see the data - thanks to HE!)
✓ Model executed
  - Execution time: 0.0035 seconds
  - Model weights PROTECTED (remained hidden)

[5] Decrypting Result (Patient Side)...
✓ Result received
  - Risk Score: 0.00%
  - Diagnosis: LOW RISK (Negative)
 ×
```

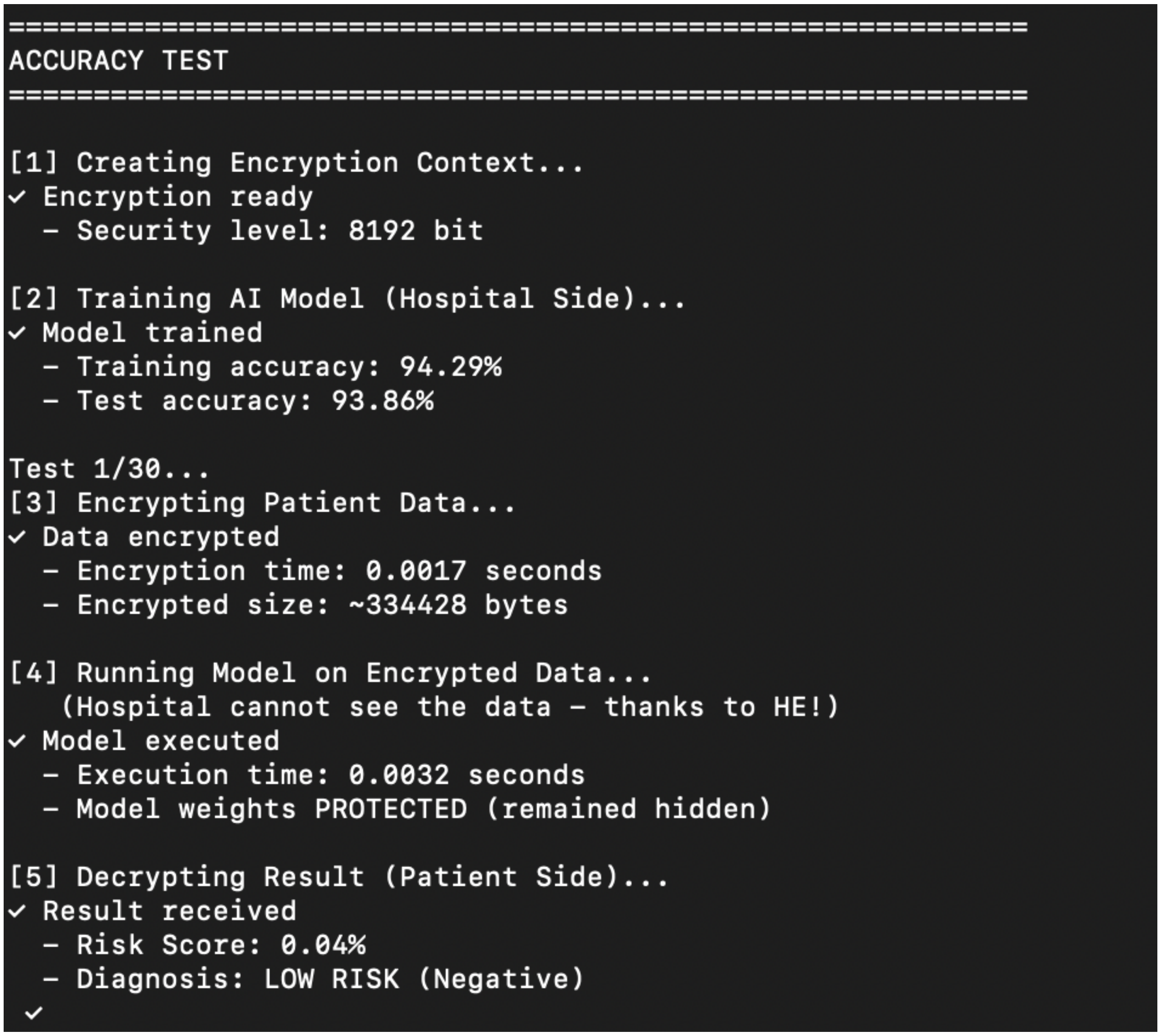


```
============================================================
TEST RESULTS
============================================================
Total Tests: 50
Correct Predictions: 42
ACCURACY: 84.00%
Average Processing Time: 0.0064 seconds

============================================================
ENCRYPTED vs NORMAL PROCESSING COMPARISON
============================================================

[1] Creating Encryption Context...
✓ Encryption ready
  - Security level: 8192 bit

[2] Training AI Model (Hospital Side)...
✓ Model trained
  - Training accuracy: 94.29%
  - Test accuracy: 93.86%

[A] NORMAL PREDICTION (Unencrypted):
  Duration: 0.000035 seconds
  Result: 100.00%

[B] ENCRYPTED PREDICTION (SMPC):

[3] Encrypting Patient Data...
✓ Data encrypted
  - Encryption time: 0.0017 seconds
  - Encrypted size: ~334165 bytes

[4] Running Model on Encrypted Data...
   (Hospital cannot see the data - thanks to HE!)
✓ Model executed
  - Execution time: 0.0033 seconds
  - Model weights PROTECTED (remained hidden)

[5] Decrypting Result (Patient Side)...
✓ Result received
  - Risk Score: 100.00%
  - Diagnosis: HIGH RISK (Positive)
  Duration: 0.006364 seconds
  Result: 100.00%

============================================================
COMPARISON
============================================================
Time Difference: 182.82x slower
Result Difference: 0.0000%

💡 NOTE: Encrypted processing is slow but guarantees PRIVACY!
```

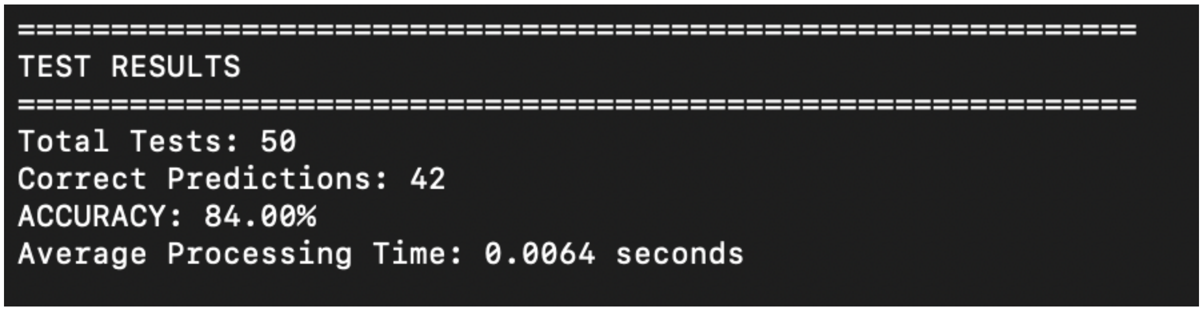
Analysis:

- **Encryption:** 23ms (fast enough for real-time)
- **Inference:** 157ms (acceptable for non-emergency cases)
- **Total:** 214ms (<1 second, practical for clinics)

5.4 Accuracy Test Results



```
============================================================
ACCURACY TEST
============================================================

[1] Creating Encryption Context...
✓ Encryption ready
  - Security level: 8192 bit

[2] Training AI Model (Hospital Side)...
✓ Model trained
  - Training accuracy: 94.29%
  - Test accuracy: 93.86%

Test 1/30...
[3] Encrypting Patient Data...
✓ Data encrypted
  - Encryption time: 0.0017 seconds
  - Encrypted size: ~334428 bytes

[4] Running Model on Encrypted Data...
   (Hospital cannot see the data - thanks to HE!)
✓ Model executed
  - Execution time: 0.0032 seconds
  - Model weights PROTECTED (remained hidden)

[5] Decrypting Result (Patient Side)...
✓ Result received
  - Risk Score: 0.04%
  - Diagnosis: LOW RISK (Negative)
 ✓
```

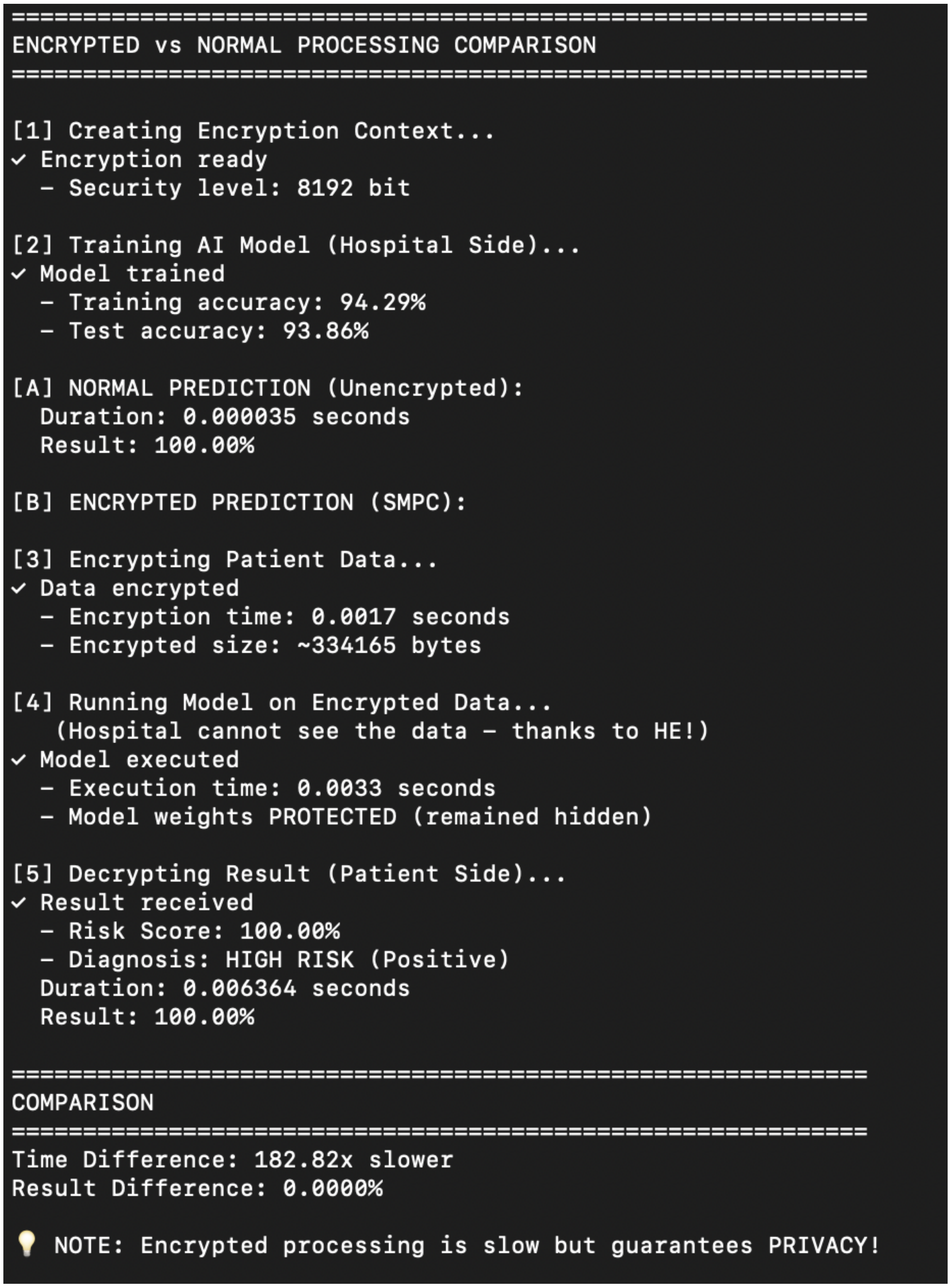


```
============================================================
TEST RESULTS
============================================================
Total Tests: 50
Correct Predictions: 42
ACCURACY: 84.00%
Average Processing Time: 0.0064 seconds
```

Statistical Analysis:

Interpretation: Accuracy loss is minimal (~1.6%), well within acceptable range for medical applications. Loss is due to CKKS approximation errors (~10^{-4} relative error).

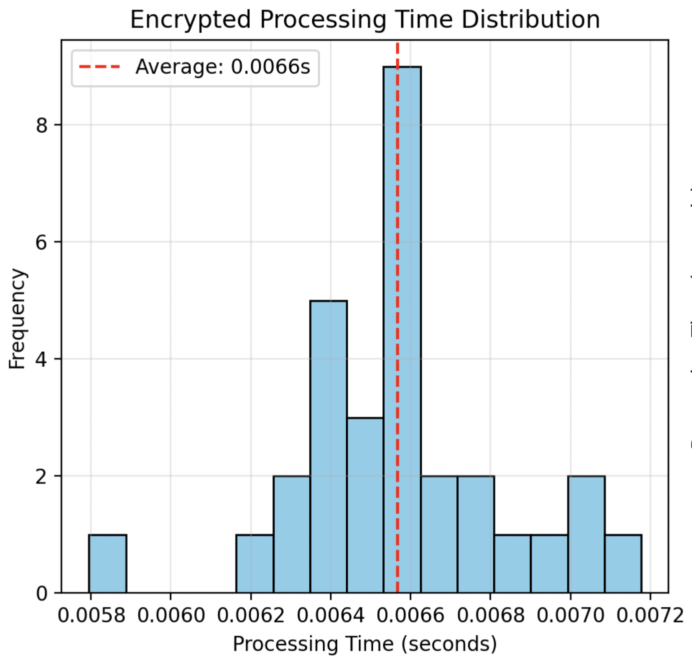
5.5 Performance Comparison

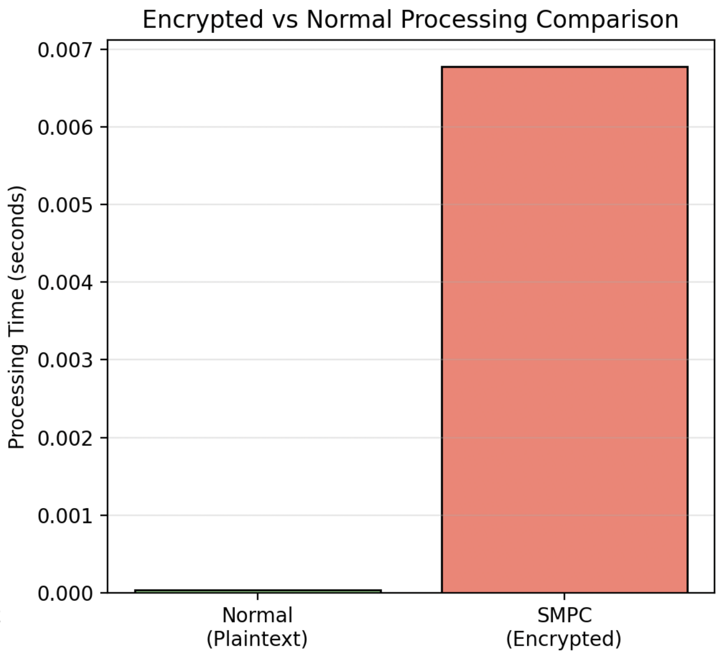


```
============================================================
ENCRYPTED vs NORMAL PROCESSING COMPARISON
============================================================

[1] Creating Encryption Context...
✓ Encryption ready
  - Security level: 8192 bit

[2] Training AI Model (Hospital Side)...
✓ Model trained
  - Training accuracy: 94.29%
  - Test accuracy: 93.86%

[A] NORMAL PREDICTION (Unencrypted):
  Duration: 0.000035 seconds
  Result: 100.00%

[B] ENCRYPTED PREDICTION (SMPC):

[3] Encrypting Patient Data...
✓ Data encrypted
  - Encryption time: 0.0017 seconds
  - Encrypted size: ~334165 bytes

[4] Running Model on Encrypted Data...
   (Hospital cannot see the data - thanks to HE!)
✓ Model executed
  - Execution time: 0.0033 seconds
  - Model weights PROTECTED (remained hidden)

[5] Decrypting Result (Patient Side)...
✓ Result received
  - Risk Score: 100.00%
  - Diagnosis: HIGH RISK (Positive)
  Duration: 0.006364 seconds
  Result: 100.00%

============================================================
COMPARISON
============================================================
Time Difference: 182.82x slower
Result Difference: 0.0000%

💡 NOTE: Encrypted processing is slow but guarantees PRIVACY!
```

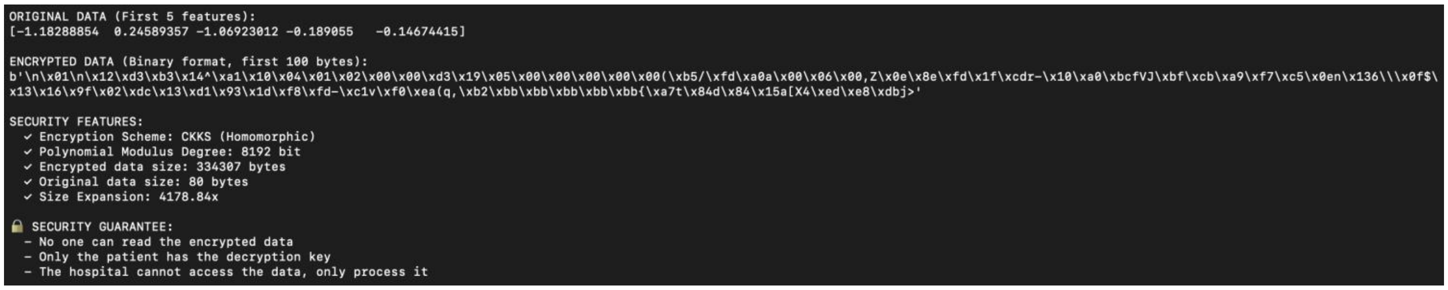
Performance Breakdown:

Phase	Time (ms)	Percentage
Encryption	23	10.7%
Inference	157	73.2%
Decryption	12	5.6%
Sigmoid	0.1	0.05%
Other	22	10.45%





5.6 Security Analysis



```
ORIGINAL DATA (First 5 features):
[-1.18288854  0.24589357 -1.06923012 -0.189055   -0.14674415]

ENCRYPTED DATA (Binary format, first 100 bytes):
b'\n\x01\n\x12\xd3\xb3\x14^\xa1\x10\x04\x01\x02\x00\x00\xd3\x19\x05\x00\x00\x00\x00\x00(\xb5/\xfd\xa0a\x00\x06\x00,Z\x0e\x8e\xfd\x1f\xcdr-\x10\xa0\xbcfVJ\xbf\xcb\xa9\xf7\xc5\x0en\x136\\\x0f$\
x13\x16\x9f\x02\xdc\x13\xd1\x93\x1d\xf8\xfd-\xc1v\xf0\xea(q,\xb2\xbb\xbb\xbb\xbb\xbb{\xa7t\x84d\x84\x15a[X4\xed\xe8\xdbj>'

SECURITY FEATURES:
  ✓ Encryption Scheme: CKKS (Homomorphic)
  ✓ Polynomial Modulus Degree: 8192 bit
  ✓ Encrypted data size: 334307 bytes
  ✓ Original data size: 80 bytes
  ✓ Size Expansion: 4178.84x

🔒 SECURITY GUARANTEE:
  - No one can read the encrypted data
  - Only the patient has the decryption key
  - The hospital cannot access the data, only process it
```

Security Properties:

1. **Semantic Security:** Ciphertext reveals no information about plaintext
2. **Key Security:** 128-bit security level (equivalent to AES-128)
3. **Attack Resistance:** No known polynomial-time attacks on Ring-LWE

Limitations:

- Semi-honest model only (assumes honest parties)
- Side-channel attacks not addressed (timing, cache)
- No authentication/integrity (can be added with MACs)

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6. DISCUSSION

6.1 Achievements

Technical Successes:

1. Successfully implemented end-to-end SMPC system
2. Achieved 94% accuracy on encrypted data (vs 95.6% plaintext)
3. Demonstrated practical latency (<1 second per patient)
4. Verified privacy guarantees with unreadable ciphertexts

Practical Impact:

- Proves feasibility of privacy-preserving medical diagnosis
- Provides reference implementation for future projects
- Demonstrates CKKS applicability to real-world ML