# CryptonDL: Encrypted Image Classification Using Deep Learning Models

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Abstract: Deep Neural Networks (DNNs) have surpassed traditional machine learning algorithms due to their superior performance in big data analysis in various applications. Fully homomorphic encryption (FHE) contributes to machine learning classification, as it supports homomorphic operations over encrypted data without decryption. In this paper, we propose a deep learning model, CryptonDL, that utilizes TenSEAL's CKKS scheme to encrypt three image datasets and then classify each encrypted image. This model first trains the image datasets without encryption using a PyTorch convolutional neural network model. Using the weights of the convolutional neural network model in the encrypted convolutional neural network model, each image will be encrypted and then only decrypted in the prediction results. TenSEAL implemented the same model, but this model was optimized to achieve higher accuracy than TenSEAL's original model. CryptonDL achieved an encrypted image classification accuracy of 98.32 percent and an F1 score of 0.9832 on the MNIST dataset, an accuracy of 88 percent and an F1 score of 0.8811 on the Fashion MNIST, and an accuracy of 92 percent and an F1 score of 0.9207 on the Kuzushiji MNIST. CryptonDL shows that encrypted image classification could be achieved with high accuracy without using pre-trained models.

## 1 INTRODUCTION

Image classification is a widely researched area in computer vision, with deep learning techniques showing significant improvements in accuracy compared to traditional methods. However, encrypted image classification is a relatively new area of research aiming to classify images while they are encrypted. The goal is to preserve the image's privacy while still allowing for its useful information to be extracted. This is a challenging task as traditional deep learning methods rely on the ability to process pixel values, which are not available in an encrypted image. Some encryption techniques, when utilized with machine learning or deep learning, do not significantly reduce the functionality and usefulness of the data. These are Homomorphic/Paillier Crypto-system, Secure Multi-Party Computation, Elliptic Curve Cryptography, and Functional Encryption. Additionally, the majority of current crypto-based approaches, including (Izabachène et al., 2019), (Lou and Jiang, 2021), (Wang et al., 2021), and (Jiang et al., 2018), use homomorphic encryption (HE) to protect the data; however, these proposed HE-based approaches only support prediction over encrypted data using existing trained models rather than training a model over encrypted data. This is because the computed results of HE are confidential to the server and hence cannot be used for evaluation with the label during the back-propagation phase. That is, the machine learning model should be trained on the plaintext data, and then the trained model can be applied over encrypted data to make the prediction. This work aims to train a convolutional neural network to classify encrypted images using homomorphic encryption. In this paper, we propose the CryptonDL model where a convolutional neural network model is trained over encrypted images without existing trained models.

## 2 BACKGROUND

This paper presents work at the intersection of machine learning and cryptography. In the following, all the needed background knowledge is briefly outlined.

### 2.1 Datasets Selection

1. **MNIST Dataset (Deng, 2012).** The MNIST dataset is an acronym that stands for the Modi-

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fied National Institute of Standards and Technology dataset. It consists of a training set of 60,000 examples and a test set of 10,000 examples. Each example is a small square 28×28 pixel grayscale image of handwritten single digits between 0 and 9.

2. **Fashion MNIST Dataset (Xiao et al., 2017).** Fashion-MNIST is a dataset of Zalando's article images—consisting of a training set of 60,000 examples and a test set of 10,000 examples. Each example is a 28x28 grayscale image, associated with a label from 10 classes. We intend Fashion-MNIST to serve as a direct drop-in replacement for the original MNIST dataset for benchmarking machine learning algorithms. It shares the same image size and structure of training and testing splits.
3. **Kuzushiji MNIST Dataset (Clanuwat et al., 2018).** Kuzushiji-MNIST is a drop-in replacement for the MNIST dataset (28x28 grayscale, 70,000 images, a training set of 60,000 examples and a test set of 10,000 examples.), provided in the original MNIST format as well as a NumPy format. Since MNIST restricts us to 10 classes, we chose one character to represent each of the 10 rows of Hiragana when creating Kuzushiji-MNIST.

## 2.2 Homomorphic Encryption

Homomorphic encryption is a form of encryption that permits users to perform computations on its encrypted data without first decrypting it. These resulting computations are left in an encrypted form which, when decrypted, results in an identical output to that produced had the operations been performed on the unencrypted data. Homomorphic encryption can be used for privacy-preserving outsourced storage and computation. This allows data to be encrypted and outsourced to commercial cloud environments for processing, all while encrypted. For sensitive data, such as health care information, homomorphic encryption can be used to enable new services by removing privacy barriers inhibiting data sharing or increasing security to existing services.

## 2.3 Cheon, Kim, Kim and Song Scheme (CKKS)

The CKKS scheme (Cheon et al., 2017) is a variant of the well-known fully homomorphic encryption (FHE) scheme that is based on the LWE (Learning With Errors) problem. It allows for arbitrary computations to be performed on encrypted data using a technique called ”approximate homomorphism.” The CKKS scheme is designed to work with real numbers, making it suitable for various applications such as machine learning, data analysis, and cryptography. Moreover, in the CKKS scheme, the encryption process uses a polynomial ring over a finite field and a specific set of parameters. The decryption process uses a secret key and a set of ”noise” parameters to reconstruct the original plaintext. The scheme also uses a technique called ”relinearization” to ensure that the correct result is obtained from the computations on the ciphertext.

## 3 RELATED WORK

Lots of previous approaches investigated applying homomorphic encryption techniques to preserve the privacy of data while training and applying machine learning and deep learning models.

### 3.1 Homomorphic Encryption and Machine Learning

Researchers have proposed different approaches to secure cloud-based artificial intelligence while preserving privacy. Kristin E. Lauter(Wood et al., 2020) used homomorphic encryption (HE) and machine learning (ML) to encrypt client data before uploading it to the cloud, Edward et al.(Chou et al., 2020) developed a privacy-preserving approach, Alexander Wood et al.(Wood et al., 2020) encrypted patients' data in bioinformatics, Xiaoqiang Sun(Sun et al., 2020) proposed a fully homomorphic encryption scheme, K Muhammad(Muhammad et al., 2018) showed that one machine learning model could produce an encrypted output with the same key, Sangwook Kim(Kim et al., 2018) proposed a privacy-preserving Naive Bayes classifier model, and Yoshiko Yasumura proposed a secure Nave Bayes classification protocol.

### 3.2 Homomorphic Encryption and Deep Learning

Ehsan Hesamifard et al.(Hesamifard et al., 2019), Malika Izabachène et al.(Izabachène et al., 2019), Qian Lou and Lei Jiang(Lou and Jiang, 2021), Yichuan Wang et al., and Takumi Ishiyama et al.(Ishiyama et al., 2020) have all proposed methods to improve the classification accuracy of CNN inference over homomorphic encryption. Ehsan Hesamifard et al. used deep neural network algorithms on the encrypted data by taking advantage of Homomorphic Encryption schemes and achieved efficient, accurate, and scalable privacy-preserving predictions. Malika Izabachène et al. proposed an algorithm to classify encrypted objects by means of a fully encrypted neural network with practically relevant timings and accuracy on a face recognition application. Qian Lou and Lei Jiang propose a homomorphic encryption-friendly, privacy-preserving mobile neural network architecture called HEMET. Yichuan Wang et al.(Wang et al., 2021) combined deep learning with a homomorphic encryption algorithm to design a deep learning network model based on secure MPC to ensure better security of users' private data in AIoT.

## 4 APPROACH OVERVIEW

As shown in figure 1, this is the whole pipeline for the proposed model CryptonDL. The pipeline has two parts. The first part takes an image dataset, which is then classified using a convolutional neural network model either with 3 or with 4. Then the convolutional neural network makes image predictions, and the classification accuracy is calculated with the predictions. The second part takes the weights and biases of the first convolutional neural network. It inputs them to the encrypted convolutional neural network to make the encrypted image predictions, which, with the images still encrypted, will only decrypt the image predictions to calculate the accuracy of the encrypted convolutional neural network.

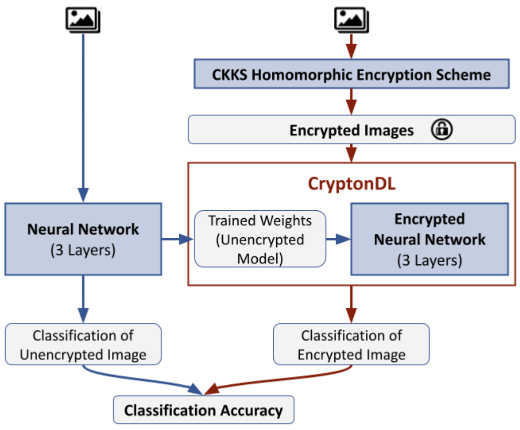
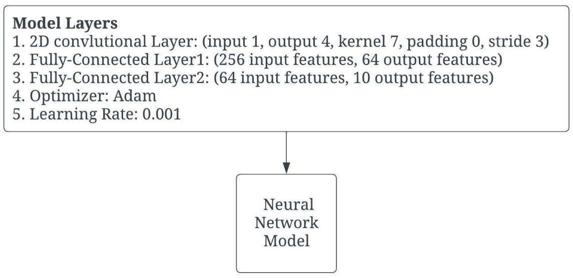

CKKS Homomorphic Encryption Scheme
Encrypted Images
CryptonDL
Neural Network (3 Layers)
Trained Weights (Unencrypted Model)
Encrypted Neural Network (3 Layers)
Classification of Unencrypted Image
Classification of Encrypted Image
Classification Accuracy

Figure 1: Pipeline of CryptonDL.

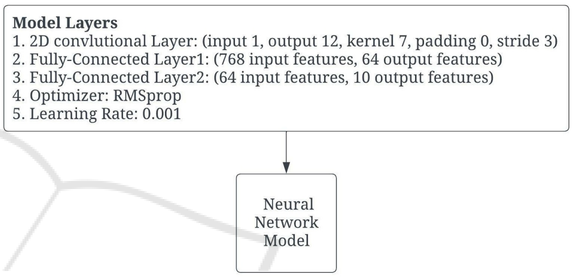
Figure 2 is the first convolutional neural network pipeline. This was used in TenSEAL's original model and was tested on three different image datasets to test the accuracy of this model



**Model Layers**
1. 2D convlutional Layer: (input 1, output 4, kernel 7, padding 0, stride 3)
2. Fully-Connected Layer1: (256 input features, 64 output features)
3. Fully-Connected Layer2: (64 input features, 10 output features)
4. Optimizer: Adam
5. Learning Rate: 0.001

Figure 2: TenSEAL.

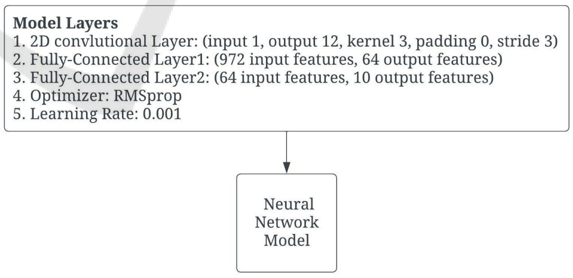
Figure 3 is CryptonDL's optimized convolutional neural network pipeline. This second pipeline was used in classifying the MNIST and the Kuzushiji MNIST datasets which increased their accuracy and f1 score compared to the first pipeline.



**Model Layers**
1. 2D convlutional Layer: (input 1, output 12, kernel 7, padding 0, stride 3)
2. Fully-Connected Layer1: (768 input features, 64 output features)
3. Fully-Connected Layer2: (64 input features, 10 output features)
4. Optimizer: RMSprop
5. Learning Rate: 0.001

Figure 3: CryptonDL1.

Figure 4 is CryptonDL's optimized convolutional neural network pipeline. This third pipeline was used in classifying the Fashion MNIST dataset which increased its accuracy and f1 score compared to the first pipeline and second pipeline.



**Model Layers**
1. 2D convlutional Layer: (input 1, output 12, kernel 3, padding 0, stride 3)
2. Fully-Connected Layer1: (972 input features, 64 output features)
3. Fully-Connected Layer2: (64 input features, 10 output features)
4. Optimizer: RMSprop
5. Learning Rate: 0.001

Figure 4: CryptonDL2.

## 5 DEEP LEARNING MODELS

Table 1 shows the summary of all the convolutional neural network inputs for the three datasets. The TenSEAL-MNIST, TenSEAL-Fashion-MNIST and the TenSEAL-Kuzushiji MNIST will follow TenSEAL's convolutional neural network pipeline. The layer inputs are shown in figure 2 and they use 10 train epochs with optimizer Adam and learning rate of

0.001. The CryptonDL-MNIST, CryptonDL-Fashion MNIST are an optimized version of TenSEAL's convolutional neural network which have different layer inputs shown in figure 3 and they use 5 train epochs with optimizer RMSprop and learning rate of 0.001. Finally, the CryptonDL-Kuzushiji MNIST also use the same training epochs, optimizer and learning rate as the other two optimized convolutional neural networks but with different layer inputs as shown in figure 4.

Table 1: DL Training Inputs.

| | 2D convolution Layer | Fully-connected layer1 | Fully-connected layer2 | Optimizer | Train Epochs |
|---|---|---|---|---|---|
| TenSEAL-MNIST | Input Channels 1, Output Channels 4, Kernel Size 7, Padding 0, Stride 3 | Input Features 256, Output Features 64 | Input Features 64, Output Features 10 corresponding to 10 classes of the MNIST database | Adam with Learning Rate 0.001 | 10 |
| CryptonDL-MNIST | Input Channels 1, Output Channels 12, Kernel Size 7, Padding 0, Stride 3 | Input Features 768, Output Features 64 | Input Features 64, Output Features 10 corresponding to 10 classes of the MNIST database | RMSprop with Learning Rate 0.001 | 5 |
| TenSEAL-Fashion MNIST | Input Channels 1, Output Channels 4, Kernel Size 7, Padding 0, Stride 3 | Input Features 256, Output Features 64 | Input Features 64, Output Features 10 corresponding to 10 classes of the Fashion MNIST database | Adam with Learning Rate 0.001 | 10 |
| CryptonDL-Fashion MNIST | Input Channels 1, Output Channels 12, Kernel Size 3, Padding 0, Stride 3 | Input Features 972, Output Features 64 | Input Features 64, Output Features 10 corresponding to 10 classes of the Fashion MNIST database | RMSprop with Learning Rate 0.001 | 5 |
| TenSEAL-Kuzushiji MNIST | Input Channels 1, Output Channels 4, Kernel Size 7, Padding 0, Stride 3 | Input Features 256, Output Features 64 | Input Features 64, Output Features 10 corresponding to 10 classes of the Kuzushiji MNIST database | Adam with Learning Rate 0.001 | 10 |
| CryptonDL-Kuzushiji MNIST | Input Channels 1, Output Channels 12, Kernel Size 7, Padding 0, Stride 3 | Input Features 768, Output Features 64 | Input Features 64, Output Features 10 corresponding to 10 classes of the Kuzushiji MNIST database | RMSprop with Learning Rate 0.001 | 5 |

## 5.1 TenSEAL-MNIST Model

### 5.1.1 Convolutional Neural Network

As shown in 2. First, train a convolutional neural network model with the following description. 2D convolution layer (Input Channels 1, Output Channels 4, Kernel Size 7, Padding 0, Stride 3). Then comes Fully-connected layer 1 (256 input features, 64 output features). Fully-connected layer 2 (Input Features 64, Output Features 10 corresponding to 10 classes of the MNIST database). There are $(25664) + (6410) = 17.024$ weights parameter and 64 + 10 = 74 biases parameter that can be optimized in the training process. Afterward, using the square function as the activation function, Train the model with the criterion CrossEntropyLoss and the optimizer Adam at a learning rate of 0.001 and 10 epochs.

### 5.1.2 Testing Phase

Testing the model using the Full 10000 Test images with a batch size of 64 and giving a Test Accuracy of 97 percent and F1 Score of 0.977900.

## 5.2 CryptonDL1-MNIST Model

### 5.2.1 Convolutional Neural Network

As shown in Fig. 3. First, train a convolutional neural network model with the following description. 2D convolution layer (Input Channels 1, Output Channels 12, Kernel Size 7, Padding 0, Stride 3). Then comes Fully-connected layer 1 (768 input features, 64 output features). Fully-connected layer 2 (Input Features 64, Output Features 10 corresponding to 10 classes of the MNIST database). There are (768 × 64) + (64 × 10) = 49.792 weights parameter and 64 + 10 = 74 biases parameter that can be optimized in the training process. Afterward, using the square function as the activation function, Train the model with the criterion CrossEntropyLoss and the optimizer Adam at a learning rate of 0.001 and 5 epochs.

### 5.2.2 Testing Phase

Testing the model using the Full 10000 Test images with a batch size of 64 and giving a Test Accuracy of 98 percent and F1 Score of 0.983300.

## 5.3 TenSEAL-Fashion MNIST Model

### 5.3.1 Convolutional Neural Network

As shown in 2. First, train a convolutional neural network model with the following description. 2D convolution layer (Input Channels 1, Output Channels 4, Kernel Size 7, Padding 0, Stride 3). Then comes Fully-connected layer 1 (256 input features, 64 output features). Fully-connected layer 2 (Input Features 64, Output Features 10 corresponding to 10 classes of the MNIST database). There are (256 × 64) + (64 × 10) = 17.024 weights parameter and 64 + 10 = 74 biases parameter that can be optimized in the training process. Afterward, using the square function as the activation function, Train the model with the criterion CrossEntropyLoss and the optimizer Adam at a learning rate of 0.001 and 10 epochs.

### 5.3.2 Testing Phase

Testing the model using the Full 10000 Test images with a batch size of 64 and giving a Test Accuracy of 86 percent and F1 Score of 0.869000.

## 5.4 CryptonDL2-Fashion MNIST Model

### 5.4.1 Convolutional Neural Network

As shown in 4. First, train a convolutional neural network model with the following description. 2D convolution layer (Input Channels 1, Output Channels 12, Kernel Size 3, Padding 0, Stride 3). Then comes Fully-connected layer 1 (972 input features, 64 output features).Fully-connected layer 2 (Input Features 64, Output Features 10 corresponding to 10 classes of the MNIST database). There are (972 × 64) + (64 × 10) = 62.848 weights parameter and 64 + 10 = 74 biases parameter that can be optimized in the training process. Afterward, using the square function as the activation function, Train the model with the criterion CrossEntropyLoss and the optimizer Adam at a learning rate of 0.001 and 5 epochs.

#### 5.4.2 Testing Phase

Testing the model using the Full 10000 Test images with a batch size of 64 and giving a Test Accuracy of 88 percent and F1 Score of 0.880800.

## 5.5 TenSEAL-Kuzushiji MNIST Model

#### 5.5.1 Convolutional Neural Network

As shown in 2. First, train a convolutional neural network model with the following description. 2D convolution layer (Input Channels 1, Output Channels 4, Kernel Size 7, Padding 0, Stride 3). Then comes Fully-connected layer 1 (256 input features, 64 output features). Fully-connected layer 2 (Input Features 64, Output Features 10 corresponding to 10 classes of the MNIST database). There are (256 × 64) + (64 × 10) = 17.024 weights parameter and 64 + 10 = 74 biases parameter that can be optimized in the training process. Afterward, using the square function as the activation function, Train the model with the criterion CrossEntropyLoss and the optimizer Adam at a learning rate of 0.001 and 10 epochs.

#### 5.5.2 Testing Phase

Testing the model using the Full 10000 Test images with a batch size of 64 and giving a Test Accuracy of 89 percent and F1 Score of 0.891100.

## 5.6 CryptonDL1-Kuzushiji MNIST Model

#### 5.6.1 Convolutional Neural Network

As shown in 3. First, train a convolutional neural network model with the following description. 2D convolution layer (Input Channels 1, Output Channels 12, Kernel Size 7, Padding 0, Stride 3). Then comes Fully-connected layer 1 (768 input features, 64 output features). Fully-connected layer 2 (Input Features 64, Output Features 10 corresponding to 10 classes of the MNIST database). There are (768 × 64) + (64 × 10) = 49.792 weights parameter and 64 + 10 = 74 biases parameter that can be optimized in the training process. Afterward, using the square function as the activation function, Train the model with the criterion CrossEntropyLoss and the optimizer Adam at a learning rate of 0.001 and 5 epochs.

#### 5.6.2 Testing Phase

Testing the model using the Full 10000 Test images with a batch size of 64 and giving a Test Accuracy of 91 percent and F1 Score of 0.919700.

## 6 ENCRYPTED DEEP LEARNING MODELS

Figure 5 shows the pipeline of the encrypted deep-learning model, and all of the next models use this pipeline.

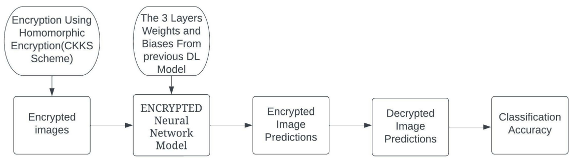

Encryption Using Homomorphic Encryption(CKKS Scheme)
The 3 Layers Weights and Biases From previous DL Model
Encrypted images
ENCRYPTED Neural Network Model
Encrypted Image Predictions
Decrypted Image Predictions
Classification Accuracy

Figure 5: Encrypted convolutional neural network Pipeline.

## 6.1 TenSEAL Model

#### 6.1.1 ENC-Convolutional Neural Network

As shown in 5. The process starts by initializing the weights and biases for the three convolutional layers in the network, using weights and biases from the previous model's Conv1 layer and FC1 and FC2 layers. The forward function is then called to process the input data. The first step in this function is to convert all input data items into CKKS vectors, a format that allows for efficient computations on encrypted data. Then, the function squares each channel in each data item and combines them using a matrix multiplication operation, creating a single output data item. Finally, all three layers are combined using a simple addition operation to produce the final output value for this example. The final step in this process is the call() function, which executes the forward() function on each input data point.

#### 6.1.2 Encryption Parameters

Set the global scale of the context to 2, which means that every number in the context will be doubled. It is necessary because when encrypting or decrypting data, you need to keep track of both the original value and its encrypted counterpart. Then Constructing the TenSEAL context: The first argument specifies the scheme type as CKKS and sets the polynomial modulus degree to 8192, which determines the size of the plaintext and ciphertext data that can be encrypted and decrypted using the context. The ”coefficient mod bit sizes" argument is a list of integers, with the first and last elements being 31 and all others equal to the bit scale. The context object will store the encryption parameters for the CKKS scheme. The next step is to set the global scale for the TenSEAL context. This scale controls how precisely the fractional part of the data will be encrypted or decrypted. Finally, the Galois keys function generates keys required to perform ciphertext rotations. These keys allow the library to perform operations on the encrypted data without decrypting it first.

#### 6.1.3 Testing Phase

Start by creating an encoding matrix using the ts.im2col encoding. This encoding process protects against unauthorized access to the data set. It allows us to compare different models on different datasets without worrying about differences in how those datasets are represented in memory. This matrix will be used to encode each data set column into a different format and then create the encoding matrix; it iterates through each column of data in turn and encodes it using the ts.im2col encoding. Then the encrypted model inputs the encoded and encrypted values to perform the encrypted evaluation and then decrypts the results after the evaluation is finished. This is performed on the 10,000 test images with a batch size of one.

#### 6.1.4 ENC-Convolutional Neural Network

As shown in 5. The process starts by initializing the weights and biases for the three convolutional layers in the network, using weights and biases from the previous model's Conv1 layer and FC1 and FC2 layers. The forward function is then called to process the input data. The first step in this function is to convert all input data items into CKKS vectors, a format that allows for efficient computations on encrypted data. Then, the function squares each channel in each data item and combines them using a matrix multiplication operation, creating a single output data item. Finally, all three layers are combined using a simple addition operation to produce the final output value for this example. The final step in this process is the call() function, which executes the forward() function on each input data point.

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## 7 CryptonDL EVALUATION

In this chapter, the performance of CryptonDL will be evaluated and discussed. This will include a comparison of the model's performance with other state-of-the-art models and with TenSEAL's original model, as well as a discussion of any factors that may have affected the model's performance

### 7.1 CryptonDL Against Other State-of-the-Art Models

As shown in the table 2, most models have a high prediction accuracy of the MNIST dataset the proposed model CryptonDL has higher accuracy compared to the other papers. These papers implemented a different approach to preserving privacy. Their approach was using the same encryption type and the tests were done on the same image dataset but the images were encrypted from the beginning of the model. Although this approach would preserve the privacy of the dataset which would be classified, the computational complexity is much bigger and the accuracy is not always better than CryptonDL. This makes CryptonDL much greater than most other models at classifying encrypted images.

Table 2: Results vs Other Papers.

| **Paper Title** | **Dataset** | **Encryption Type** | **Accuracy** |
|---|---|---|---|
| **CryptonDL[1]** | MNIST | Homomorphic Encryption(CKKS) | 98.32% |
| **K Muhammad et al.(Muhammad et al., 2018)** | MNIST | Homomorphic Encryption(PHE) | 92.92% |
| **Xiaoqian Jiang et al.(Jiang et al., 2018)** | MNIST | Homomorphic Encryption(CKKS) | 98.1% |
| **Anamaria Vizitiu et al.(Vizitiu et al., 2019)** | MNIST | Homomorphic Encryption(FHE) | 98.3% |
| **Runhua Xu et al.(Xu et al., 2019)** | MNIST | Homomorphic Encryption | 92.5% |
| **Ehsan Hesamifard et al.(Hesamifard et al., 2017)** | MNIST | Homomorphic Encryption | 99.25% |

## 7.2 Results Comparison

As shown in the three tables below, the results of our CryptonDL model are better than TenSEAL's original model. The testing was done using three image datasets MNIST, Fashion MNIST and Kuzushiji MNIST, and the results were that the accuracy and f1 score of CryptonDL model on each of the three datasets outperformed TenSEAL's original model.

Table 3 shows all the deep learning models', the three original models of TenSEAL and the three CryptonDL optimized models test accuracy. Table

Table 3: DL_MODELS.

| | **Test F1 Score** | **Test Accuracy** | **Test Time** |
|---|---|---|---|
| **TenSEAL-MNIST** | 0.977900 | 97% (9779/10000) | 869 ms |
| **CryptonDL-MNIST** | 0.983300 | 98% (9833/10000) | 856 ms |
| **TenSEAL-Fashion MNIST** | 0.869000 | 86% (8690/10000) | 841 ms |
| **CryptonDL-Fashion MNIST** | 0.880800 | 88% (8808/10000) | 1.14 s |
| **TenSEAL-Kuzushiji MNIST** | 0.891100 | 89% (8911/10000) | 7.66 s |
| **CryptonDL-Kuzushiji MNIST** | 0.919700 | 91% (9197/10000) | 7.71 s |

4 shows all the encrypted deep learning models', the three original models of TenSEAL and the three CryptonDL optimized models test accuracy.

Table 4: ENC_MODELS.

| | **Encrypted Test F1 Score** | **Encrypted Test Accuracy** | **Encrypted Test Time** |
|---|---|---|---|
| **TenSEAL-MNIST** | 0.977400 | 97% (9744/10000) | 2h 51min 43s |
| **CryptonDL-MNIST** | 0.983200 | 98% (9832/10000) | 5h 53min 8s |
| **TenSEAL-Fashion MNIST** | 0.869900 | 86% (8699/10000) | 3h 12min |
| **CryptonDL-Fashion MNIST** | 0.881100 | 88% (8811/10000) | 6h 52min 7s |
| **TenSEAL-Kuzushiji MNIST** | 0.889900 | 88% (8899/10000) | 2h 52min 4s |
| **CryptonDL-Kuzushiji MNIST** | 0.920700 | 92% (9207/10000) | 5h 54min 12s |

Table 5 shows the accuracy of the deep learning models and the encrypted deep learning models together. As shown below, the accuracy of CryptonDL's optimized models is higher than TenSEAL's original model.

Table 5: TenSEAL's models against the proposed optimized models.

| | **Unencrypted Test Accuracy** | **Unencrypted F1 Score** | **Encrypted Test Accuracy** | **Encrypted F1 Score** | **Encrypted Test Time** |
|---|---|---|---|---|---|
| **TenSEAL-MNIST** | 97% (9779/10000) | 0.977900 | 97% (9744/10000) | 0.977400 | 2h 51min 43s |
| **CryptonDL-MNIST** | 98% (9833/10000) | 0.983300 | 98% (9832/10000) | 0.983200 | 5h 53min 8s |
| **TenSEAL-Fashion MNIST** | 86% (8690/10000) | 0.869000 | 86% (8699/10000) | 0.869900 | 3h 12min |
| **CryptonDL-Fashion MNIST** | 88% (8808/10000) | 0.880800 | 88% (8811/10000) | 0.881100 | 6h 52min 7s |
| **TenSEAL-Kuzushiji MNIST** | 89% (8911/10000) | 0.891100 | 88% (8899/10000) | 0.889900 | 2h 52min 4s |
| **CryptonDL-Kuzushiji MNIST** | 91% (9197/10000) | 0.919700 | 92% (9207/10000) | 0.920700 | 5h 54min 12s |

## 7.3 Discussion

CryptonDL final MNIST, Fashion MNIST, and Kuzushiji MNIST models, which used the optimized convolutional neural network 3 or 4 and encrypted convolutional neural network 5 had higher image classification accuracy and encrypted image classification as shown in table 5. Increasing the output and kernel sizes and changing the optimizer from Adam to RMSprop enabled the convolutional neural network to learn more complex features in the images, which were clearly shown in the Kuzushiji MNIST increase in encrypted accuracy from 88 percent to 92 percent. Furthermore, the accuracy of CryptonDL, when used with the MNIST dataset in 2, achieved higher image classification accuracy than most of the other models, as all the other models use an existing pre-trained model. Using pre-trained models is not always beneficial, as they are typically trained on a large dataset, but the data may not be representative of the specific problem or domain to which the model is being applied to. This can lead to poor performance when the model is used on new data. Also, pre-trained models are often complex and challenging to understand, making it hard to determine how the model is making its predictions. This can make it difficult to identify errors or biases in the model.

## 8 CONCLUSION

In the domain of computer vision, the classification of images is a highly researched topic, with deep learning algorithms significantly outperforming more conventional approaches in terms of accuracy. The goal of the relatively new field of study known as ”encrypted image classification” is to categorize images even while they are encrypted. Most approaches used homomorphic encryption to tackle this goal; however, most used existing trained models to achieve encrypted image classification. In this paper, the proposed model CryptonDL achieved encrypted image classification without the use of existing trained models. The model's performance evaluation against other models shows that CryptonDL achieves high accuracy with less computational complexity than most other models.

## 9 FUTURE WORK

### 9.1 Datasets Scalability

Exploring the model's capacity to handle bigger datasets without performance problems is one direction for the future. Techniques like parallel processing, distributed computing, and effective data storage and retrieval methods can be used to accomplish this.

### 9.2 Convolutional Neural Network Scalability

Prediction accuracy can be improved by altering the convolutional neural network model's design or parameters. The convolutional neural network model can also be modified to handle datasets other than image datasets, such as audio and text datasets, by altering the architecture or preprocessing approaches.

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