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Multi Class Image Classification Using Machine Learning and Deep Quantum Neural Networks

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Abstract—This project will create a binary classification system for images using a "Deep Quantum Neural Network" implemented into a "Django based web development architecture." A "CNN (Convolutional Neural Network)" will exist for feature extraction, with "Quantum Neural Network Processing" done through "PyTorch and PennyLane." Visualization and analysis will occur for data sets, with visualization available for real-time test images through a "User Canvas." Cross entropy will optimize accuracy in the "binary classify system," and user and admin functionalities are split for data handling to ensure images are retrieved effectively through the system's architecture.

Keywords-Binary Image Classification, Deep Learning, Deep Quantum Neural Network, MNIST Dataset.

INTRODUCTION

Due to the rapid growth of digital images, proper images grouping and classification have become a critical issue in order to organize images correctly in a given system. However, classification of images in a precise way has become a critical issue, considering the complexities of images, as images have a large number of features that are considered during classification. For this project, a structured system has been created in order to classify images, which has been implemented by using the Django framework in order to create a website where images are classified in a proper way, considering a precise way of classification, where images are classified as a binary type.

The techniques of deep learning prominently feature in the project, especially using Convolutional Neural Networks in feature extraction concerning images. The CNN is quite effective in handling high- dimensional image data, and it can easily learn how to capture meaningful features from large image datasets. In the project, there is the use of deep neural networks in processing images and then using optimization techniques like the cross-entropy loss function. The use of data augmentation and evaluability is employed in ensuring effective generalization.

The deep convolutional neural network presents exceptional assistance in cutting-edge techniques of image categorization and processing. The enhanced convolutional neural networks offer strong support in the categorization of images of higher resolutions. The deep neural networks can be utilized when developing models with large input datasets. When training an image input dataset on deep neural networks, parameters and image feature sets with a large number of images are utilized. For the identification of images, deep neural networks harness the features of the image dataset and fuse them.

This study uses the Django framework for managing user authentication, role-based access control, and interaction with the image classification model. The architecture has a separate module for administrators and a module for users so that the datasets, users who maintainability whereby coordination between the front-end interface and back-end machine learning logic is smoothly executed.

The system also supports facilities for dataset visualization where users can perform exploratory data analysis to better understand the distribution of images before the actual classification occurs. For example, users can use specific views to examine the dataset and the images for better interpretation. This bridges the gap between the raw images and the actual modeling classification, enhancing the interpretability of the classification within the application.

Also, the use of the cross entropy approach helps optimize the model, while the canvas interface clearly illustrates the performance of the model on real-time images.

I. LITERATURE REVIEW

Earlier image classification methods heavily depended on locally derived feature descriptors such as Local Binary Pattern (LBP), parallel slope shapes, and wavelet descriptions of texture to carry out image representation. These methods were somehow efficient in image classification tasks on small databases but failed to perform generalizations in more complicated image structures and high-dimensional imaging features. An ensemble classifier such as Support Vector Machine (SVM), random forest classifier, etc., has to be used to enhance image classification accuracy, thereby making a heavy dependency on noise proneness of these feature descriptors in image classification tasks.

With the development and expansion of deep learning methodologies, Convolutional Neural Networks have emerged and have gained popularity for their potential and efficiency in image classification tasks due to their ability to learn semantic features and hierarchical features for image data. They have been efficient across a variety of domains for image and vision-based tasks and have demonstrated good potential and efficiency for medical image classification and other image-based tasks. Techniques such as dropout and batch normalization have also become popular for their ability to enhance and boost the generality and robustness of deep learning and prediction performance.

Recent studies have been conducted on the integration of principles of Quantum Computing with the deep learning approach in an attempt to break the limitations associated with classical neural networks. As a result, the application of both the Quantum Neural Network and Quantum-Classical Network in the improvement of learning capacity has been confirmed through the improvement in classification accuracy relative to classical deep learning methods. With the motivation of the latest trends in deep learning arising from the latest studies on Quantum Neural Network- based systems for image classification, the project applies a hybrid Quantum-Classical system based on the Deep Quantum Neural Network approach in the classification of binary image classification datasets with Django-based systems.

III . METHODOLOGY

The developed methodology is centered on building a hybrid classical-quantum learning paradigm for binary image classification. The system will be implemented within a Django-based web application user interface that allows for user interactions and the execution of the developed image classification system. The images for the backend environment will either be coming from existing data sets or an interactive user canvas. The images processed

for classification will be fed to the deep learning-based environment.

During classical learning phase in CNN models, features are learned from input images in a meaningful and high-level representation by CNN. CNN models are particularly useful in handling image-related problems because they can automatically learn various patterns based on image pixels in a natural way. Furthermore, these features learned can maximize differences between actual class labels and predicted class labels in binary classification using a cross- entropy function during training of models.
unstable lighting conditions or facial appearance variations.

In order to enhance the ability, the new methodology uses the classical model that has been established and is known as the CNN, while incorporating the new model that has been proposed and is known as the Deep QNN. In the proposed new model, unlike the classical model, the value of the quantum bit is used in the calculations instead of the classical bit. For instance, the classical bit can assume any value ranging from 0 to 1. However, the value that is assumed by the quantum bit can be any value that is the composition of both 0 and 1 as per the new principle that has been proposed and is known as the principle of superposition.

Overall, the entire classification mechanism employs a general structural workflow wherein an input image can be obtained, CNN features can be extracted from the data, quantum neural processing can be enacted on the CNN features, cross-entropy optimization can be executed during the binary classification task itself, and the results of this entire process can be visualized for the users through the usage of the Django interface in real time.

A. Procedure

Quantum Image Processing has an Image Processing workflow as well. Quantum Image Processing technology is quite similar in nature when considering other conventional Image Processing technologies. At the very beginning, while discussing the conventional Image Processing technology, it can be stated that an image can have a number of representations by putting forward a number of image encodings, where the image representation can take place

considering the ways an image can be encoded by considering the color provided to the image pixel. At the same time, a number of modifications can take place with regard to the need to crop an image, enhance the image, and/or filter the image. Under these circumstances, a number of image processing can take place by considering the needs to retrieve the required data from the image.

For this quantum-based processing to occur, the information has to, in some way, be encapsulated in a quantum state. At this time of writing, this available technology can only maintain machines or devices that have a small qubit count where qubits exist coherently for a brief period of time. Thus, in one sense, what primarily occurs in this Quantum Machine Learning process is to encode classical information onto a quantum state. Quantum Data Encoding or Quantum Embedding is mainly what this Quantum Machine Learning process carries out on the classical information passed to this process. Even more so, Quantum Machine Learning's algorithm is dependent upon Quantum Data Encoding.

1) In order to function according to the constraints and requirements imposed by current NISQ devices, a data representation is necessary and must be efficient, requiring only a small number of qubits and quantum gate operations. As qubits have a tendency towards decoherence and gate operations have a tendency to cause errors due to their susceptibility to noise, a minimal number of quantum gate operations need to be present to generate the required quantum state. Quantum data encoding is broadly classified under two categories: one is the use of digital encoding through qubit string encoding, and analogue encoding is used for the encoding of information to the values present in a Hilbert state.

The number of qubits remains as low as possible due to the existence of images that are in a standardized and binary form and which contain no redundant qualities.

The parallel operations are avoided through proper differentiation of admin logic, user logic, and quantum paths to ensure no excessive circuit width is used.

The use of information in a way that reveals its essence matches the appropriate encoding of information during the process from digital- based encoding in order to carry out the authentication, data set management, as well as exploratory data analysis, to name a few, to analogue-based encoding in which classification of images takes place according to the concept.

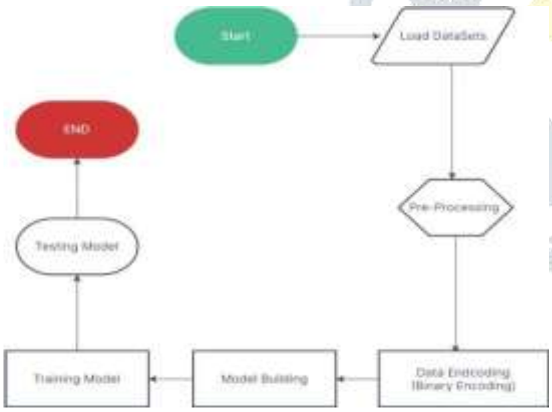
Overall, the use of source code is indicative of an adequate balance between the use of 'digital' and 'analogue' encoding schemes for the purpose of classical control, data handling, and arithmetic operations. On the other hand, the analogue encoding is required to successfully encode the data for the purpose of efficient performance of any 'learning' operation.

1) En Code:

It appears as if the conventional data presented in the form of the user image, as found in the MNIST dataset, or the user input canvas is first processed through the Django view before it is made compatible with the quantum system as presented in the User Test Canvas MNIST itself or the MnistTorchQNN.

2) Processing:

The processed encoded information goes now to the quantum routine that has been defined in the following file: MnistTorchQNNThe input is processed



by a quantum model.

3) Measurement:

Accordingly, this classic output, produced as a consequence of quantum processing, will then be transmitted again to this view as a prediction tool.

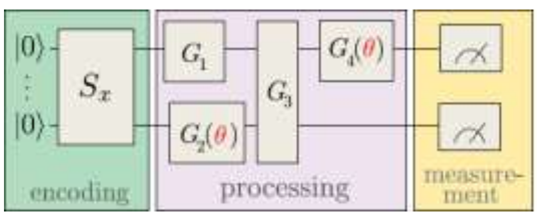


Fig1: Typical Quantum Machine Learning Steps

A closer look at the whole encoding process itself will now follow. Remember that the whole encoding process is shown in its entirety in Figure 1 above. One way to input a specific input into a specific quantum algorithm in the form of a quantum state is to run the circuit for a specific quantum state on the input. As mentioned above, this circuit was already prepared in the classical pre processing stage and was used in the construction of the state preparation circuit itself, as shown above.

Fig2: Classical Preprocessing Steps

B. *Implementation and Results*

In this project, the proposed quantum machine learning models are implemented using a simulated quantum environment, as evidenced in the code with regard to the quantum-related application routines. The implementation process for quantum machine learning closely follows a workflow related to the implementation of classical machine learning models, including data preparation, execution of the model, and generation of results in a successive manner. The stages in the implementation are evident with regard to various views and functions defined in the source code.

a) Datasets:

For the experimentation purpose, the MNIST dataset comes into play, and it is confirmed by the way the dataset is handled in the codes, where specific functions such as User Test Canvas MNIST or MnistTorchQNN have been used. The MNIST dataset is one of the most widely used datasets where images of handwritten numbers are used for the experimentation purpose, containing 60,000 images for training the models and 10,000 images for testing the performance of the quantum machine learning algorithm used within the project. algorithm used within the project.

Fig3: Process Flow Chart

b) Pre Processing:

Most generally speaking, the set of data used is made of ten classes of various forms of images. However, in the study itself, it can be noted that a particular form of binary image classification is the one being discussed. Most generally speaking, the set of data used.

Actual processing of the said set of data, particularly the MNIST set of data, there can be noted the involvement of maintaining two classes of images then discarding the rest. Afterward, the said set of images is then converted so as to be in grayscale form. This converted set of images being the ones set for input in the said quantum circuit is then converted to the 2 x 2 form.

Data Encoding: For encoding images into quantum inputs, images are reshaped into 1x4x1 matrix. Then binary encoding technique is applied with threshold value 0.5 and finally converted into quantum input using quantum circuit of grid qubit of size 2 x 2.

c) Encoding of Data:

First off, the images will have to undergo a resizing to a 1 X 4 X 1 shape before a binary encoding process involving a threshold value of0.5 will begin and convert the images entirely to binary. Then, these images will have to undergo a conversion to a quantum input form. Here, under the normal process, a quantum circuit will have to be introduced, and a 2 X 2 qubit grid will have to be incorporated to enable the images to enter the model.

d) Model Building:

To prepare the quantum model, quantum gate operations for single-qubit quantum gate and two-qubit quantum gate operations are carried out in the proposed system. Over the proposed model, the X gate has been used in the encoding process, whereas the H gate is employed in the measurement process. Apart from the above- mentioned quantum gates employed in the proposed implementation, other quantum operations proposed in the model are the incorporation of the quantum operations carried out in the hidden layer, that is, the inclusion of the XX gate operations and the ZZ gate operations. Having finished the above- mentioned operations, the proposed model is as represented below in Figure 4.

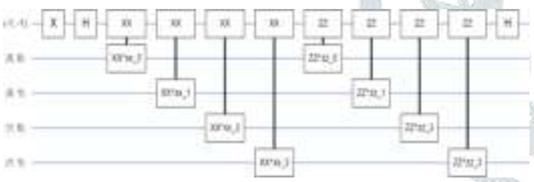


Fig4: Typical Quantum Circuit

B) Trainig and Testing:

Hinge loss and hinge accuracy are used as the major metrics during the training and test phases of the model. The RMSprop optimizer is applied to minimize the loss function and hence increase the performance of the model. The available dataset is divided in such a way that 30% of the data is kept for validation, while the remaining portion is utilized for training-the ultimate way of having effective evaluation while learning.

C) Results Assessment:

Hinge loss basically is a penalty in nature, rather than in estimating probabilities. This increases the classification margin while reducing misclassification errors but does not offer reliable probability outputs. As the hinge loss decreases, the number of misclassifications across the decision margin decreases and the classification performance as they increases accordingly. The approach results in higher accuracy with the introduction of certain sparsity, though it offers less sensitivity to the interpretation based on probabilities. The hinge loss values for the proposed model are depicted in Figure.

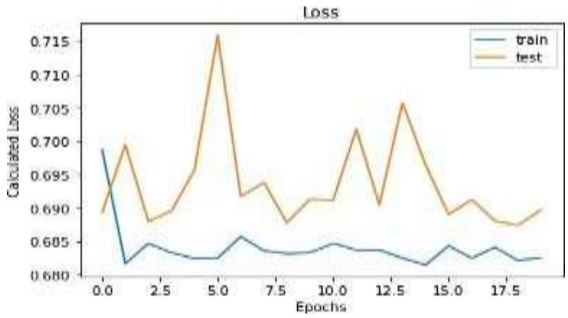


Fig5: Epochs vs Loss Curve

IV. CONCLUSION

This paper proposes a binary image classification system based on the quantum neural network. The system is developed using a web-based platform. The proposed system combines classical pre

processing with the execution of quantum circuits for image classification in MNIST. Although the experiment has shown the possibility of quantum machine learning, the results of accuracy and loss values have shown some limitations in the current model.

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