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ENHANCED COS-HADAMARD TRANSFORM FOR COVID-19 PREDICTION USING REINFORCEMENT LEARNING TECHNIQUE

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ABSTRACT

Recent technological developments have the path for Machine Learning and Deep Learning-based techniques to be used in almost every domain of life. The precision of Machine Learning and Deep learning techniques make it possible to be used in the medical field for classification and detection of various diseases. Since COVID-19 is highly contagious, diagnosis using chest X-ray is considered safe in various situations. In this study, ML and DL based technique to classify COVID-19 infection from other non-COVID-19 infections are considered. Since the outbreak of the COVID-19 pandemic, worldwide research efforts have focused on using artificial intelligence (AI) technologies on various medical data of COVID-19–positive patients in order to identify and classify with various aspects of the disease, with promising reported results. This study aims to examine the severity of this problem by evaluating machine learning and Reinforcement learning classification models trained to classify COVID-19–positive patients on X-ray datasets from different countries. The research articles discussed reveal that various Feature Extraction and Classification techniques help to classify the normal and COVID-19. The X-ray dataset undergoes Pre-processing and Data Augmentation methods followed by train and test, finally compared on the basis of different performance metrics. The results show that, Enhanced Cos-Hadamard Transform Feature Extraction Approach with Q-Learning classification model achieved 88.57% accuracy.

Keywords: Fourier Transform, Wavelet Transform, Cosine Transform, Hadamard Transform, Enhanced Cos-Hadamard Transform

1. INTRODUCTION

A number of pneumonia cases with an unknown origin were recorded in the Wuhan Hubei region of China in December 2019 [1]. It was eventually identified as the severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2, formerly known as the 2019 new coronavirus or COVID-19), which produced serious public health difficulties and eventually turned into a significant global outbreak. Recent estimates indicate that there are millions of proven cases in both India and the United States, and the number is continually rising.

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Following H1N1 (2009), polio (2014), Ebola in West Africa (2014), Zika (2016), and Ebola in the Democratic Republic of the Congo (2019), the WHO also proclaimed COVID-19 to be the sixth public health emergency of global concern on January 13, 2020 [2][39]. Additionally, it was discovered that the novel corona, viral pneumonia is comparable to another severe acute respiratory syndrome brought on by the Middle East Respiratory Syndrome (MERS) coronavirus and that it can also bring on more severe form known as Acute Respiratory Distress Syndrome (ARDS). To stop transmission and make diagnosis and treatment easier, consensus, criteria, and guidelines were being developed. The comparatively gradual onset of symptoms, which allowed for broad transmission by asymptomatic carriers, is partly to blame for the infection's rapid occurrences. This virus spread quickly across the globe and gave rise to a pandemic [3, 4] along with the global connectivity of today's travel society.

According to previous reports of coronavirus infections, the COVID-19 pneumonia's radiological imaging shows significant consolidation and interstitial inflammation, as well as the destruction of the pulmonary parenchyma. The term "interstitial lung disease" (ILD) refers to a group of more than 200 different chronic lung illnesses characterised by inflammation of the lung tissue, often known as pulmonary fibrosis. Lung fibrosis makes the lungs rigid, which hinders the ability of the air sacs areas within an organism where air is always present—to transport and distribute oxygen into the circulation. This eventually may cause breathing to become permanently impossible. The ILDs are heterogeneous diseases from a histology standpoint, but they typically share clinical symptoms with one another or with other types of lung conditions. A low diagnosis accuracy and considerable inter- and intra-observer variability, which has been reported to be as high as 50%, are also caused by the substantial amount of radiological data that radiologists are forced to analyse (in the absence of stringent clinical guidelines).

Reverse transcription-polymerase chain reaction (RT-PCR) assays of nasopharyngeal swabs are the most popular method for diagnosing COVID-19 infections [5]. A timely diagnosis of infected individuals may be hampered by the lengthy testing process, high false-negative rate [6], and lack of RT-PCR assay kits during the early stages of the outbreak. The lung with COVID-19 infections can be imaged well using computed tomography (CT) and chest X-rays (CXR). Contrary to the swab test, the results of a CT and CXR show the precise location of the suspected pathology as well as the severity of the damage. The characteristic pathology of a CXR is the bilateral distribution of hazy, peripheral lung opacities that also contain air space consolidation [7]. Imaging provides the benefit of having good sensitivity, a quick turnaround, and the ability to show the degree of lung infection. The drawback of imaging is that, due to its low specificity, it is difficult to differentiate between different forms of lung infections, particularly when the lung infection is severe.

2. REVIEW OF LITERATURE

Systems for computer-aided diagnosis (CAD) can help radiologists make more accurate diagnoses. The hand-crafted or learned features that are based on the texture, shape, and morphological aspects of the lung are currently being used by researchers for detection. However, selecting the right classifier that can effectively handle the lung's feature spaces is frequently important and difficult. Bayesian networks (BNs), support vector machines (SVM), artificial neural networks (ANNs), K-Nearest Neighbours (K-NN), and Adaboost, decision trees (DTs) are the conventional approaches for image recognition. Such hand-crafted features as texture, SIFT, entropy, morphology, elliptic Fourier descriptors (EFDs), geometry, density of pixels, and off-the-shelf classifiers as mentioned in [10] are needed to compute these machine-learning approaches [8, 9]. Additionally, feature-based machine learning (ML) techniques are referred to as non-deep learning techniques. These non-deep

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learning techniques have a wide range of benefits, including the diagnosis of cancer, psychological disorders, and neurodegenerative illnesses. [9,11-14]. However, the main drawback of non-deep learning approaches is that they depend on the feature extraction stage, which makes it challenging to locate the most pertinent feature that is required to get the best outcome.

One of the most promising classification tools is machine learning [15]. Machine learning, in its simplest form, is a model that seeks to identify the unidentified structure, relationship, or function between input and output data. These relationships are typically difficult for explicit algorithms to discover through an automatic learning process. Machine learning techniques are used to forecast future mortality rates and potential confirmed cases [16]. Two categories can be used to separate machine learning. The genetic algorithm is used in the first part to determine the ideal weight for data fusion of multi-node perception results and to remove unusable nodes, and the fault nodes are found in the second part using a fault identification neural network [17]. Supervised Learning (SL), Un-supervised Learning (UL), and Reinforcement Learning (RL) are only a few of the learning paradigms used in machine learning, which is a branch of artificial intelligence (AI) [18]. Classification, regression, clustering, anomaly detection, dimensionality reduction, and reward maximisation are typical components of ML models [19]. Because the ML algorithms are trained using labelled data sets and the SL paradigm, they have a ground-truth output (continuous or discrete) for each input. In contrast, there is no ground-truth output in UL [20], and the algorithms often look for patterns in the data. Raising the cumulative reward seeks to make Reinforcement Learning more suitable for sequential decision-making tasks[21]. Regression and classification are features of supervised learning, while unsupervised learning also includes cluster analysis and dimensionality reduction, as well as classification and control in Reinforcement Learning (RL).

Recent work on edge computing and the detection of (COVID-19) Cases has been approached from three different angles. The imaging processes that can motivate machine-learning techniques that can enable radiologists who want an analysis of complicated imaging and text data are thought to be the algorithms for the recognition of activity from machine learning and the methodologies which employed in edge computing. There are models for the novel COVID-19 that can analyse medical images and identify COVID-19 [18]. Machine learning (ML), one of the applications of artificial intelligence (AI), has been successfully used in a variety of medical fields for the detection of novel genotype-phenotype associations and diagnosis. These applications also had an impact on evaluation, prediction, disease classification, transcriptomic analysis, and lowering the death ratio [19].

This study concentrated on articles that used machine learning applications in the COVID-19 disease for various purposes with various algorithms [22]. Of the 16 articles, 14 used supervised learning, one used unsupervised learning, and one used both supervised and unsupervised learning, and both produced accurate results. Five of these articles used the logistic regression algorithm, and all of them showed encouraging results in the COVID-19 health care applications and involvement. The studies used various machine-learning and Deep learning algorithms in different countries and by different authors, but they were all related to the COVID-19 pandemic. The remaining 14 publications utilised various supervised and unsupervised learning algorithms, and all of the models produced accurate findings, with the exception of three articles that used artificial neural networks (ANN), which also produced effective results.

An accuracy of 77.50 percent and an area under the receiver operating characteristics curve (AUC) value of 99 percent were attained [23] when the holdout approach was used to divide the training and testing data. In a different study [24], the 75 features of 485 samples

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of COVID-19 patients were subjected to the XGBoost algorithm. A 90% classification accuracy for COVID-19 patients was attained when cross-validation was utilised to divide the training and testing samples [24]. Finally, only the features that are the most informative will be kept. As a result of this phase, classifiers will function well because the number of characteristics has decreased and become more valuable. There are many different feature selection techniques, including filter-based [25], forward selection, backward elimination, recursive feature elimination (RFE), principal component analysis (PCA), linear discriminant analysis (LDA), [26, 27], and optimization techniques [28–30]. Some of these methods were applied to the selection of Covid-19 detection characteristics from X-ray pictures [31, 32].

Efficient and accurate detection of Coronavirus Disease 2019 (COVID-19) is essential for improving long-term patient survival rates, understanding the course of the pandemic, and providing appropriate patient care. Many convolutional neural network-based models struggle with overfitting and the expressiveness problem, and training these models always requires a lot of resources, even with all the recent efforts in medical imaging. This work introduces a novel method for predicting COVID-19 from X-ray thorax pictures using Xception enhanced with state-of-the-art transfer learning techniques. According to our experimental results, the suggested model outperforms well-known models in the field, such as Xception, VGG-16, and ResNet, in terms of predictive accuracy. This study represents a major advancement in improving COVID-19 identification using an advanced and effective imaging methodology [34].

In general, it is thought that no nation was adequately equipped to deal with a pandemic, especially one of the size of the COVID-19 epidemic. Together with its lengthy incubation period, SARS-CoV-2's special capacity to spread from asymptomatic individuals before symptoms appear makes it challenging for nations to stop the disease's spread. Hospital transmission rates, a general lack of essential money and resources, and community opposition to outbreak mitigation measures like travel bans, public face mask use, and social distance are further obstacles to containing the spread of Covid-19.The significance of political will in preventing epidemics is among the most important lessons to be drawn from the COVID-19 pandemic. Many people around the world were also made aware of the dysfunctional and overburdened health systems in many regions of the world by the COVID-19 pandemic.Public health systems must continue to be dedicated to creating sufficient surveillance programs, timely diagnostic methods, and strong research projects that can identify and comprehend the fundamental biology and, if required, treat new organisms in order to make sure that the world is better equipped to handle the next new infectious agent [35].

The spread of COVID-19 throughout the nation's numerous regions and provinces is a key focus. The researchers propose a hybrid model architecture for analysing and optimising COVID-19 data throughout the entire nation, using the current COVID-19 pandemic as a guide. An ARIMA model using susceptible-infectious-removed and susceptible-exposed-infectious-removed (SEIR) models is used to analyse the exploration and death rate of COVID-19. A hybrid model approach addresses the shortcomings of the SEIR model's excessive number of tuning parameters as well as the logistic model's inability to predict the number of confirmed diagnoses. Recurrent neural networks (RNN), long short-term memory (LSTM), multilayer perceptrons (MLP), logistic regression (LR), autoregressive integrating moving average model (ARIMA), support vector regression (SVR), and gate recurrent units (GRU) are all used for the same objective. These models are displayed using root mean square error, mean absolute error, and mean absolute percentage error. The study's conclusions describe the number of quarantines, fatality rates, new COVID-19 cases, and the implementation of public self-protection measures to lessen the pandemic. The results can be

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used by government officials to inform future decisions about sickness prevention and control [36].

Equation-based modelling (EBM) and agent-based modelling (ABM) are two modelling techniques that we examine in this work in order to comprehend the dynamics of infectious diseases in the population. To do this, a comparative analysis of different methods was carried out, and we outlined the benefits and drawbacks of each. Both methods were used in two case studies on the COVID-19 pandemic's spread. The findings indicate that while agent-based models are more realistic and closely resemble biology, differential equation-based models are quicker but still more basic. These results suggest that combining the two methods could be a worthwhile compromise [37].

The agent-based approach to service design has a distinct benefit over traditional micro service-based design since it can both provide reactive solutions and proactively anticipate and address potential issues. This and other benefits have made multi-agent-based intelligent network service design a popular and cutting-edge paradigm in network research. A softwarized intelligent network architecture and design ideas that use agents as building blocks have recently been proposed for the upcoming 6G networks. However, despite these developments, there are currently not enough modelling settings to evaluate the performance of multi-agent systems in these softwarized networks. In this work, we use the PADE framework to describe the continuous generation and deployment of many network service agents. To help with this, we have also provided a link to the project on GitHub. As possible evaluation scenarios, a number of machine learning and deep learning approaches are employed in the implementation. This experimental environment can also be used for a variety of clever algorithm investigations [38].

Since the virus persisted in spreading in spite of community efforts, a COVID-19 epidemic might result in a severe shortage of medical supplies, medical personnel, and of course, COVID-19 diagnostic kits. It can be difficult to give suspected COVID-19 patients the best care possible if there is a shortage of COVID-19 testing kits, which can impede early disease detection. For this reason, it is necessary to develop an automated prediction system that can determine if a person has COVID-19. Datasets, pertinent software, and machine learning classification methods are needed to create a COVID-19 prediction model. Supervised, unsupervised, and reinforcement learning are the three subcategories of machine learning. Using labelled datasets where examples are appropriately labelled according to their various classes supervised learning teaches machines [40].

The Random Forest Classifier object from scikit-learn's feature significance attribute was used to pick features for the independent variables in this study. A statistic known as Gini important can be used to assess the significance of features in a Random Forest. When a certain feature is utilized for splitting, this metric calculates the overall decrease in the dataset's Gini impurity. A characteristic is considered more essential for the model if its Gini significance is higher [41].

The abnormal 4:1 ratio between the COVID-19 "Yes" class (4,383 samples) and the "No" class (1,051 occurrences) in our dataset led to the identification of the data imbalance problem. Prediction bias can result from data imbalance because machine learning classifiers may become unduly accustomed to the COVID-19 "Yes" class due to its enormous sample size. Consequently, there is a considerable chance that the model will skew its predictions by predicting COVID-19 as "Yes" in the majority of cases [43]. We used a method called SMOTE (Synthetic Minority Over-Sampling Technique) to solve this. SMOTE is an oversampling technique that interpolates between pre-existing examples from the minority class to create synthetic samples for that class [42].

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With fewer samples in the dataset, this method successfully raises the class's representation. Achieving a high accuracy rate, reducing the error rate, and avoiding classification bias all depend on this kind of dataset balancing. Following the implementation of SMOTE, the dataset's total sample count rose to 8,766. The COVID-19 "Yes" class comprises 4,383 of these samples, while the COVID-19 "No" class now includes the remaining 4,383 samples. After the dataset was balanced, we divided it using 8:2 ratio, meaning that 80% of the samples were used as the training dataset to create the COVID-19 prediction model and the remaining 20% were reserved for performance testing.

3. DATASET DESCRIPTION

The dataset that was used to train and test the suggested technique is accessible to everyone on Kaggle [33]. The dataset utilised in this study was obtained from Kaggle following three changes to the original dataset. The aforementioned dataset is made up of a number of smaller datasets that fall into four categories: COVID-19, Normal and viral pneumonia. Given that the used dataset was created by combining many datasets, it is crucial to go into detail about its composition. Every class is produced by combining various sub-datasets. There are 5,863 X-Ray images (JPEG) and 2 categories (Covid-19/Normal) collected from four different sources.

3.1 Data augmentation

Deep learning models usually demand a significant volume of training data. Image augmentation technology has been generally used in computer vision and has attracted attention since the advent of deep learning. The more the data, the better the model’s performance, and because COVID-19 is still a newly emerging disease, so far, no appropriate dataset is publicly available. Therefore, we have to use data augmentation as it is a very powerful technique to artificially generate a large dataset. We apply three augmentation strategies: Random Rotation with an angle between − 10 and 10 degrees, random noise, and horizontal flips (means reversing the columns of pixels). In fact, image noising is a significant way that permits our model to figure out how to isolate signal from noise in an image. As a result, the model is more adaptable to informational changes.

3.2 Data pre-processing

During data pre-processing, it is possible to resize the X-ray images. It’s due to the fact that the various algorithms require different image inputs. The images should be normalized according to the given model standards. The input images were in different original size, therefore they were all processed and they were made uniform by changing the dimensions to 224×224 pixels.

4. METHODOLOGY

There are four primary stages to this architecture. First, the input X-ray dataset is sent to data pre-processing so that the images can be resized and normalised. The features are then extracted using a variety of feature extraction techniques. The most significant elements in the images are then chosen using feature selection techniques, and finally, various machine learning and deep learning classifiers are used to create the models.

4.1 Feature Extraction

Dimensionality reduction is frequently used to condense a bigger data collection into its most distinct elements, allowing for the inclusion of pertinent information and the description of the data with fewer features. This makes data with lots of features or high dimensionality properly shown and makes it easier to carry out Reinforcement Learning classification. These methods include Enhanced Cos-Hadamard Transform Feature Extraction Approach. The features from the medical images are extracted using distinct feature extraction methods in this research. The different feature parameters from the medical images were recovered using the feature extraction approach.

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4.1.1 Fourier Transform

The Fourier Transform is a mathematical technique used to decompose a signal into its constituent frequencies. It converts a time-domain signal into a frequency-domain representation, revealing the signal's frequency components. This is particularly useful for analyzing signals that are periodic or stationary, where the frequency content is more important than the specific time variations. In the frequency domain, a signal is represented as a sum of sine and cosine functions of different frequencies, amplitudes, and phases. Fourier analysis is widely applied in signal processing, audio processing, image compression, and communications, among others, to detect periodicity, filter noise, or compress data. However, one limitation of the Fourier Transform is that it assumes the signal is stationary, meaning it doesn't capture the time-varying nature of non-stationary signals like speech or a transient event, which is where other transforms like the Wavelet Transform come into play.

4.1.2 Wavelet Transform

The Wavelet Transform is a more flexible alternative to the Fourier Transform, as it provides a time-frequency representation of a signal. Unlike Fourier, which decomposes signals using infinite sinusoids, the Wavelet Transform uses localized wavelets to capture both high and low-frequency features at different time scales. This means it can analyze both the frequency and time content of a signal simultaneously, making it particularly effective for signals that change over time (non-stationary signals). There are two main types: Continuous Wavelet Transform (CWT), which provides a fine-grained analysis across scales, and Discrete Wavelet Transform (DWT), which is more computationally efficient and often used in applications like image compression and signal denoising. The Wavelet Transform is widely used in speech processing, medical signal analysis (e.g., EEG, ECG), and audio denoising, as it provides a detailed analysis of both transient and periodic features that change over time.

4.1.3 Cosine Transform

The Discrete Cosine Transform (DCT) is a type of Fourier-related transform that uses only cosine functions to represent a signal. It is similar to the Fourier Transform but restricted to real-valued functions. The DCT is particularly efficient for tasks involving compression, as it has excellent energy compaction properties—most of the signal's energy is concentrated in just a few DCT coefficients. This makes it ideal for image and video compression formats such as JPEG and MPEG, where reducing the size of the data without significant loss of quality is crucial. The DCT is widely used in signal processing, particularly for applications where data needs to be compressed or transmitted efficiently, such as in audio compression (e.g., MP3) and image compression. Its ability to capture significant information in a small number of coefficients makes it one of the most effective transforms for compressing multimedia content while preserving quality.

4.1.4 Hadamard Transform

The Hadamard Transform is a mathematical operation that transforms a signal or vector using a Hadamard matrix, which is composed of +1 and -1 values. It is a simpler and more computationally efficient alternative to transforms like the Fourier or Cosine Transforms, particularly when speed and parallel computation are important. The Hadamard Transform is a linear transformation that is used in various fields, including signal processing, image processing, data compression, and error-correcting codes. Unlike Fourier-based transforms, which use sinusoidal functions, the Hadamard Transform performs its decomposition using simple binary values, making it very fast to compute, especially for large datasets. It is used in applications like fast algorithms, quantum computing, and communications systems, where quick processing of large-scale data is critical. The

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Hadamard Transform's simplicity makes it useful in situations where computational efficiency is paramount, especially in real-time systems or large-scale data processing.

Hadamard Transform Algorithm:

The Hadamard Transform is applied to a vector by multiplying it with the Hadamard matrix. Here's a step-by-step breakdown of the process:

Step 1: Construct the Hadamard Matrix

Begin with the Hadamard matrix of order 2 (i.e., H_2) and recursively build larger matrices of the form H_2^n by using the following rule:

$$H_{2^{n+1}} = \begin{pmatrix} H_{2^n} & H_{2^n} \\ H_{2^n} & -H_{2^n} \end{pmatrix}$$

Step 2: Multiply the Input Vector by the Hadamard Matrix

Once you have the appropriate Hadamard matrix H_n the Hadamard Transform is applied by multiplying the input vector x with the matrix H_n:

$y=H_n.x$

Where:

x is the input signal (a vector of length n).

H_n is the Hadamard matrix of order n.

y is the resulting transformed vector.

Step 3: Normalize (Optional)

The Hadamard matrix is typically scaled by a factor of 1\√n to make it orthonormal. In this case, the transformed vector would be:

$$y = \frac{1}{\sqrt{n}} H_n \cdot x$$

Step 4: Inverse Hadamard Transform

To recover the original signal, you apply the inverse Hadamard Transform, which is simply the transpose of the Hadamard matrix, scaled by 1/n

$$x = \frac{1}{n} H_n^T \cdot y$$

:

4.1.5 Enhanced Cos-Hadamard Transform

Feature extraction is a critical task in many machine learning, image processing, and signal processing applications. The goal is to extract meaningful patterns or representations from raw data that are useful for tasks such as classification, clustering, or compression. The combination of the Hadamard Transform and the Discrete Cosine Transform (DCT) can provide an effective approach for feature extraction, leveraging both the orthogonality and energy compaction properties of these transforms.

Here, I'll propose an approach for feature extraction that combines the Hadamard transform and DCT. The key idea is to extract features by applying these transforms sequentially or in parallel, taking advantage of both the symmetry and sparsity of Hadamard and the frequency domain compactness of DCT. Step-by-Step Proposed Approach for Feature Extraction:

Step 1: Data Representation

The first step in any feature extraction pipeline is to represent the data in a suitable form, typically a matrix or vector. For example, if the data is an image, we can represent the image as a 2D matrix where each pixel corresponds to an entry in the matrix. For time-series data, each time point corresponds to a feature in a vector.

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Let X is the raw input data matrix, which can have dimensions m×n where m is the number of data points (or samples) and n is the number of features or dimensions in each sample.

Step 2: Hadamard Transform (HT)

The Hadamard Transform is an orthogonal transform that operates by performing element-wise multiplication of the input data with a Hadamard matrix. It is typically used for simplifying data in ways that preserve the original structure but reduce the redundancy.

1. **Construct the Hadamard matrix**: The Hadamard matrix H_n is a square matrix of size n×n where n is a power of 2. The Hadamard matrix is recursively constructed, and it contains entries of ±1. For instance, a 2x2 Hadamard matrix is:

$$H_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

2. **Apply the Hadamard Transform**: The HT of a vector x is given by:

$$HT(x) = H_n \cdot x$$

This step will generate a transformed version of the data, potentially making it easier to identify patterns.

Step 3: Cosine Transform (CT)

The Cosine Transform, particularly the Discrete Cosine Transform (DCT)**,** is widely used in signal processing and image compression. It helps to concentrate the signal energy into a few coefficients, which can be particularly useful in feature extraction by reducing dimensionality.

1. **Apply DCT**: For each sample, apply the DCT to the data. This is typically done using a form of the DCT (e.g., DCT-II for compression) that transforms the signal into a series of cosine waves of varying frequencies. The 1D DCT for a signal x is given by:

$$DCT(x)_k = \sum_{n=0}^{N-1} x_n \cdot \cos\left(\frac{\pi}{N}\left(n+\frac{1}{2}\right)k\right), \quad k = 0, 1, \ldots, N-1$$

For multi-dimensional data, the 2D DCT can be applied, which involves taking the DCT in both the row and column directions for image-like data.

2. **Select significant coefficients**: Often, after performing DCT, only the first few coefficients (those with the highest energy) are retained, as they typically carry the most significant information about the original signal. This helps in reducing the dimensionality of the data.

Step 4: Feature Combination

At this point, we have two transformed representations of the original data:

1. The Hadamard Transformed data X_{HT}
2. The Cosine Transformed data X_{CT}

These can be combined in different ways:

1. **Concatenation**: You can concatenate the features from both transformations into a single feature vector for each data point. This increases the dimensionality but may capture more comprehensive features.

$$\text{Features} = \text{Concatenate}(X_{HT}, X_{CT})$$

2. **Feature Selection/Dimensionality Reduction**: You could apply further techniques such as PCA (Principal Component Analysis) or t-SNE (t-Distributed Stochastic

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Neighbor Embedding) to reduce the dimensionality and select the most relevant features after concatenation.

Step 5: Normalization and Final Feature Set

After combining the features, it is essential to normalize the features to ensure that each feature contributes equally to downstream machine learning tasks. Standard normalization methods such as Min-Max scaling or Z-score normalization can be applied. Finally, the resulting feature set is ready for use in machine learning models like classification, regression, clustering, or deep learning models.

4.2 REINFORCEMENT LEARNING CLASSIFICATION

Reinforcement learning (RL) isn't typically used for classification, but it can be applied in certain scenarios, such as sequential decision-making tasks. In RL, an agent interacts with an environment and learns to take actions that maximize cumulative rewards. In a classification context, class labels can be treated as actions, and the agent learns to select the correct class based on input features. The reward signal could reflect whether the classification is correct or not. RL may also be useful in adaptive settings, like when dealing with changing data distributions or feature selection, though it's less common compared to traditional supervised learning.

4.2.1 Markov Decision Process (MDP) Algorithm

A Markov Decision Process (MDP) is a framework for decision-making in environments where outcomes are partly random and partly under the control of the agent. It is defined by the tuple:

- **S**: Set of states.
- A: Set of actions.
- P(s'|s, a): Transition probability from states to s′ when taking action a.
- R(s, a, s'): Reward function.
- γ: Discount factor (importance of future rewards).

1. **Initialization**:
    - Initialize the value function V(s).
    - Initialize the policy π(s).
2. **Value Iteration**:
    - Update the value function for each state using the Bellman equation**.**
    - Extract the optimal policy after value convergence.
3. **Policy Iteration**:
    - Alternate between policy evaluation (computing the value function for a fixed policy) and policy improvement (improving the policy based on the value function).
4. **Q-learning (Model-Free Approach)**:
    - Learn the Q-values (state-action values) through trial and error.
    - Update Q-values using the Q-learning update rule and eventually extract the optimal policy.
5. **SARSA (On-Policy Algorithm)**:
    - Similar to Q-learning but updates Q-values based on the action actually taken (rather than the greedy action).

4.2.2 Deep Q-Networks

Deep Q-Networks (DQN) is an advanced reinforcement learning algorithm that combines Q-learning with deep neural networks to solve complex environments, especially those with high-dimensional input spaces like images. Here's a short breakdown:

1. **Q-learning with Neural Networks**:

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- ❖ Instead of using a Q-table (which is impractical for large state spaces), DQN uses a neural network to approximate the Q-values for each action in a given state. This allows it to handle large or continuous state spaces.

2. **Experience Replay**:
   - ❖ To stabilize training, DQN stores past experiences (state, action, reward, next state) in a replay buffer. The agent randomly samples mini-batches from this buffer for training, which helps break correlations between consecutive experiences and improves learning efficiency.
3. **Target Network**:
   - ❖ DQN uses two networks: the Q-network (which is being trained) and a target network (a fixed copy of the Q-network). The target network is used to compute the target Q-value during updates, and its weights are periodically updated from the Q-network to prevent instability.
4. **Learning Update**:
   - ❖ The network is trained to minimize the difference between the predicted Q-values and the target Q-values using mean squared error.

4.2.3 Q-Learning

Q-learning is a model-free reinforcement learning algorithm used to find the optimal action-selection policy for a given environment. It enables an agent to learn how to behave by interacting with its environment and receiving rewards or penalties for its actions. The key idea behind Q-learning is to estimate the Q-value (quality) for each action in each state, which represents the expected future rewards an agent can get by taking that action in that state and following the optimal policy thereafter.

Here's a simplified explanation of how Q-learning works:

- ❖ **Initialize Q-values**: Initialize a Q-table with arbitrary values (usually zeros), where each entry represents a state-action pair (Q(s, a)).
- ❖ **Interact with the Environment**: The agent chooses an action based on the current Q-values, often using an epsilon-greedy strategy (selecting the action with the highest Q-value most of the time but occasionally choosing a random action to explore new possibilities).
- ❖ **Update Q-values**: After taking an action and receiving a reward, the agent updates the Q-value for that state-action pair using the Bellman equation:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right]$$

  Where:
  - Q(s,a) is the current Q-value of the state-action pair.
  - α is the learning rate (controls how much new information is considered).
  - r is the immediate reward received after taking action an in states.
  - γ is the discount factor (how much future rewards are considered).
  - Max a′Q(s′,a′) is the maximum Q-value of the next state's′.
- ❖ **Repeat**: The process continues as the agent explores and exploits its environment, gradually improving its Q-values until they converge to the optimal policy.

5. PERFORMANCE METRICS

(i) Accuracy

It is most common performance metric for classification algorithms. It may be defined as the number of correct predictions made as a ratio of all predictions made. We can easily calculate it by confusion matrix with the help of following formula:

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$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

(ii) Sensitivity

Recall may be defined as the number of positives returned by our ML model. We can easily calculate it by confusion matrix with the help of following formula –

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

(iii) Specificity

Specificity, in contrast to recall, may be defined as the number of negatives returned by our ML model. We can easily calculate it by confusion matrix with the help of following formula –

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}}$$

(iv) F Measure

The F-measure is calculated as the harmonic mean of precision and recall, giving each the same weighting. It allows a model to be evaluated taking both the precision and recall into account using a single score, which is helpful when describing the performance of the model and in comparing models

$$F\text{ - measure} = \frac{2*\text{Recall}*\text{Precision}}{\text{Recall} + \text{Precision}}$$

(v) ROC

An ROC curve is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters:

- ✓ True Positive Rate
- ✓ False Positive Rate

$$\text{TPR} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

(vi) Error Rate

The error rate measures the proportion of incorrect predictions made by the model.

$$\text{Error Rate} = \frac{\text{Number of Incorrect Predictions}}{\text{Total Number of Predictions}} = 1 - \text{Accuracy}$$

6. RESULTS AND DISCUSSION

In this research applied Proposed Hadamard and Cosine Transform Feature Extraction Approach using Q-Learning to classify COVID-19 from COVID-19 and normal.

Table.1 - Performance metrics for three classifiers using Enhanced Cos-Hadamard

Feature Extraction Method	Classification Method	Accuracy	Sensitivity	Specificity	F Measure	ROC	Error Rate

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Enhanced Cos-Hadamard	Markov Decision Process	80.71	82	89	56	93	20.32
	Deep Q-Networks	81.43	81	89	45	91	31.93
	Q-Learning	**88.57**	89	92	46	94	18.06

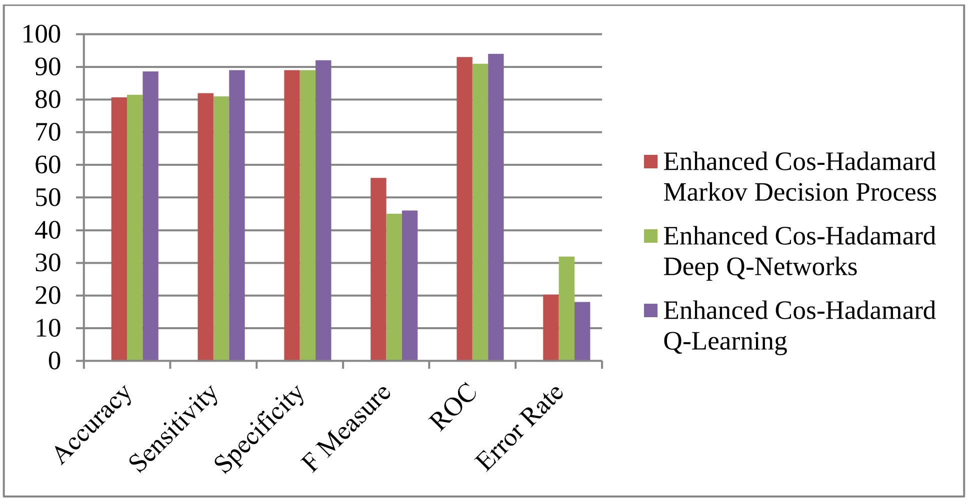

Fig.1 - Graphical Representation for three classifiers using Enhanced Cos-Hadamard

Table.2 - Accuracy for three classifiers using Enhanced Cos-Hadamard

Reinforcement Learning Classification Techniques	**Enhanced Cos-Hadamard Transform**
Markov Decision Process	80.71
Deep Q-Networks	81.43
Q-Learning	**88.57**

The results presented highlight the performance of three reinforcement learning classification techniques—Markov Decision Process (MDP)**,** Deep Q-Networks (DQN), and Q-Learning when applied to the Enhanced Cos-Hadamard Transform feature extraction method. Q-Learning demonstrates the highest performance, achieving an accuracy of 88.57%, indicating that it is the most effective technique in correctly classifying instances compared to the other methods. This suggests that Q-Learning is well-suited for leveraging the Enhanced Cos-Hadamard Transform to make accurate predictions.

7. CONCLUSION

Based on the experiment and in-depth study, a number of issues are addressed and investigated. First, the only dataset offered for COIVD-19 as a solution is the small sample X-ray image, which has a limited public image dataset. However, this problem brings up another difficulty, namely the need for a small sample for feature extraction and training.

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Secondly, based on the experiments, a comparison of three Reinforcement classification models was done, and the outcome showed that the Multi-Layer Perceptron is the best model. Traditional machine learning methods have been used in this work. Four models have been created using traditional machine learning to help classify medical images (Covid-19, Pneumonia, and Normal). All models are evaluated in terms of various parameters, including Accuracy, Recall, Specificity, F-1 Score, ROC and Error Rate. It can be inferred from the experiment results that all the models performed satisfactorily, with machine learning models achieving the accuracy of 88.57% in Enhanced Cos-Hadamard using Q-Learning**.** Future research will focus on developing a hybrid multimodal Reinforcement learning system for COVID-19 classification in an effort to get better outcomes.

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