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Exploring the Impact of Different Potential Update Rules on the Performance of Spiking Neural Networks

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Term Project

ELİF SENA ÖZCAN

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This is to certify that we have read the term project **Exploring the Impact of Different Potential Update Rules on the Performance of Spiking Neural Networks** submitted by **Elif Sena Ozcan**, and it has been judged to be successful, in scope and in quality, at the defense exam and accepted by our jury as a TERM PROJECT.

APPROVED BY:

Advisor: **PhD. Assistant Professor. Osman Gokalp**
İzmir Kâtip Çelebi University

Date of Defense: June 15, 2023

Declaration of Authorship

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Date: 15.06.2023

Exploring the Impact of Different Potential Update Rules on the Performance of Spiking Neural Networks

Abstract

Spiking neural networks (SNNs) have grown in popularity in recent years due to their ability to mimic the activity of actual neurons, making them suitable for a wide range of machine learning applications. In this study, we explore the impact of different potential update rules on the performance of SNNs for COVID-19 classification from CT scan images. The COVID-19 pandemic has brought unprecedented challenges to the healthcare system worldwide, and early detection of the disease is crucial to controlling its spread. CT scan imaging has emerged as a powerful tool for COVID-19 diagnosis, as it provides high-resolution images that reveal lung abnormalities associated with the disease. Accordingly, we have attempted to model an SNN based on different neuron models using a variety of deep learning packages. In particular, we examine four distinct potential update rules, including the classical IF and several variants of an exponential integrate-and-fire model that we present. Using SNNs, we extract characteristics from CT scan pictures and input them into a supervised classifier for decision making. With both an accuracy and an F1 score of 0.83, the proposed model surpasses several other approaches, including the classical IF model.

Keywords: Spiking Neural Networks, COVID-19, CT Scans, Computer Vision, Deep Learning, Integrate-and-fire Model

Farklı Potansiyel Güncelleme Kurallarının İğnecikli Sinir Ağlarının Performansı Üzerindeki Etkisini Keşfetme

Öz

Son yıllarda, spiking sinir ağlar (SNN'ler), gerçek nöronların faaliyetini taklit edebilme yetenekleri nedeniyle popülerlik kazanmış ve geniş bir makine öğrenimi uygulama yelpazesine uygun hale gelmiştir. Bu çalışmada, farklı potansiyel güncelleme kurallarının SNN'lerin COVID-19 sınıflandırması için performansına olan etkisini araştırıyoruz. COVID-19 pandemisi, sağlık sistemine eşi benzeri görülmemiş zorluklar getirmiş olup, hastalığın yayılmasını kontrol etmek için erken teşhis önemlidir. CT tarama görüntüleme, hastalıkla ilişkili akciğer anormalliklerini gösteren yüksek çözünürlüklü görüntüler sunması nedeniyle COVID-19 teşhisi için güçlü bir araç olarak ortaya çıkmıştır. Bu doğrultuda, farklı sinir hücresi modelleri kullanarak SNN tabanlı bir model oluşturmayı denedik ve çeşitli derin öğrenme paketlerini kullandık. Özellikle, klasik İF modeli ve sunmuş olduğumuz birkaç üstel entegre-et ve ateşleme modelinin farklı potansiyel güncelleme kurallarını inceliyoruz. SNN'ler kullanarak CT tarama resimlerinden özellikler çıkarıyor ve denetimli bir sınıflandırıcıya giriş olarak vererek karar verme sürecinde kullanıyoruz. Önerilen modelin doğruluk ve F1 puanı 0,83 olup, klasik İF modeli dahil birçok başka yaklaşımı geride bırakmaktadır.

Anahtar Kelimeler: COVID-19, Derin Öğrenme, İğnecikli Sinir Ağları

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List of Abbreviations

COVID-19	Coronavirus Disease of 2019
CT Scans	Computed Tomography Scans
rRT-PCR	Real-time Reverse Transcription Polymerase Chain Reaction
AI	Artificial Intelligence
ANN	Artificial Neural Network
DCNN	Deep Convolutional Neural Network
SNN	Spiking Neural Network
STDP	Spike-timing-dependent Plasticity
ME-IF	Modified Exponential IF
IF	Integrate-and-Fire
GPU	Graphics Processing Unit

Chapter 1

Introduction

1.1 COVID-19 Outbreak

COVID-19 is an infectious disease originated from the SARS-CoV-2 virus. The very first recorded case was discovered in December 2019 in Wuhan, China [1]. The infection rapidly spread throughout the world, resulting in the COVID-19 pandemic. [2]. There have already been many fatalities around the world, and the prevalence of infections continues to rise. Additionally, concerning economical aspects, it has caused extreme damage in almost the whole world. Precautionary measures including social isolation, quarantine, etc., were strongly advised since no vaccine had been developed back at that time. Broad diagnostics of infected people are essential components of disease prevention, so that they would quickly be identified, qurantined, and treated. A real-time reverse transcription polymerase chain reaction (rRT-PCR) has been the ideal method of testing for this disease. X-rays and CT scans of the chest are sometimes used, despite the fact that they are not advised. When it comes to initial screening, nevertheless, X-Ray and CT scans can be extremely useful. This paper presents a convolutional neural network, based on a modified neuron model, for analyzing CT scan images to detect COVID-19 patients.

1.2 Deep Convolutional Neural Networks

Artificial Intelligence (AI) systems are mainly developed based on deep learning, which is a machine learning approach. By analyzing structured/unstructured data via consecutive neuron layers, artificial neural networks (ANNs) can perform complicated non-linear analysis. Deep Convolutional Neural Networks (DCNNs), which are based on three-dimensional neuron layering, have been used to solve complex computer vision problems, including pattern recognition and classification problems, that are beyond the scope of traditional analytical approaches. This three dimensional layering approach significantly decreases the number of neurons needed to process an image, compared to traditional ANNs. DCNNs have significantly improved computer vision capabilities given the emergence of immense processing capabilities and AI-based techniques that take use of it. In many situations, such models prove to be more effective than human eyesight in many object detection tasks. To this day, academics from all around the globe are still interested in learning more about how brains operate in order to develop computer algorithms that are just as efficient and accurate as these models.

1.3 Spiking Neural Networks for Image Classification

Spiking neural networks (SNNs) have been suggested as a variety of designs and computational models in the neuroscience area of imitating how the biological brain works. However, even if DCNNs surpass SNNs in terms of detection performance, it is clear that the present trend of increasing attention to biologically based SNNs has little to do with performance. Earlier, the issue was one of processing capacity; now, and for the foreseeable future, the focus must be on environmentally friendly, power-efficient approaches and hardware. Over a million years, the human's brain has been evolving, and as consequence of evolutionary optimization, the average human brain only uses around 20 watts of electricity. This is about the same as what a typical laptop uses in terms of electricity. It's beyond our present skills to fully comprehend this neurological efficiency, but researchers have extensively used algorithms based on spikes to develop massively parallel neuromorphic chips that are power-efficient [3, 4]. Spike-timing-dependent plasticity (STDP), a biologically inspired learning technique [5, 6], have proven to be unexpectedly feasible to hardware and could be the ideal fit for online learning [7]. Besides these factors, researchers have been driven to attempt other techniques of applying SNNs to diverse visual tasks by the intrinsic capacity of SNNs to handle spatiotemporal patterns. Using structural neural networks in a systematic way is among the most prevalent techniques, but choosing the appropriate neuron model, and the tuning of additional hyperparameters involves a much research. Concerning neurologically based techniques, SNNs based on STDP are the most realistic in a biological manner. These common visual elements may be reliably extracted from image or video data thanks to STDP. However, following the unsupervised learning algorithm used for feature extraction, supervised learning algorithms and classifiers are frequently needed for the decisionmaking process.

For the detection of COVID-19, computed tomography has proved itself to be a useful tool. These images have been used to create models that can be used to identify individuals with COVID-19. Nevertheless, only a few scholars have contemplated using SNNs in this capacity. Within that study, we have implemented a modified exponential IF (ME-IF) neuron model to build a deep convolutional spiking neural network (DCSNN) based on a network architecture inspired from [8]. Initially, each input picture is processed by passing through a convolution layer that uses Gabor filters at different spatiotemporal scales. Thereafter, by encoding the images based on intensity to latency [9], a waveform of spike-based signals is produced and propagated towards the the next layer. The spikes waveform ultimately enters the final layer upon going through a sequence of convolution and pooling layers featuring neurons that can only fire once. Finally, in order to classify build the classification model, those features extracted from the neural networks are then used in a supervised learning classifier, such as Random Forest Classifier, XGBoost Classifier, or Naïve Bayesian classifiers.

1.4 Neuron Models and Potential Update Rules

For decades, the study of neural activity and its underlying causes has been a key issue in neuroscience. Researchers have sought to imitate the activity of biological neurons in order to construct more efficient and powerful computing models since the advent of artificial intelligence and machine learning. Because of its capacity to simulate the activity of genuine neurons, Spiking Neural Networks (SNNs) have emerged as a viable alternative to classic artificial neural networks. The neuron model, which is responsible for processing and sending information, is an important component of SNNs. The performance of SNNs is strongly dependent on the neuron model used and the potential update rules that regulate the neurons' functioning. We investigate the effect of several possible update rules on the performance of SNNs for COVID-19 classification from CT scan pictures in this work. We investigate four different possible update rules, including the conventional Integrate-and-Fire (IF) model and three versions of an exponential integrate-and-fire model that we propose. Our research seeks to provide light on the implications of various update rules on the performance of SNNs for image classification tasks, with a particular emphasis on COVID-19 detection.

Chapter 2

Literature Review

Deep learning, playing a key role in the computer vision, and medical imaging field, has garnered substantial attention over the past years. The use of radiology, including CT scans, and the like to identify COVID-19 has also been done utilising approaches based on deep learning algorithms.

A CNN was utilised in [10] to determine if COVID-19 patients were infected or not. Using multi-objective differential evolution, the researchers were able to fine tune the CNN's starting settings. On chest CT scans, the authors used their methodology and the latest machine learning methods to conduct extensive tests. The researchers concluded that their suggested model could detect the patients with COVID-19 with a satisfactory classification accuracy of over 90 percent.

Using chest CT scans for COVID-19 identification, another research [11] proposes an AFS-DF (adaptive feature selection guided deep forest) methodology. A method known as deep forest was utilised to extract the features' highlevel representations from such small-scale datasets, which the authors first assessed. Additionally, the paper presented a method to decrease the redundant features total count in the deep forest model by selecting just the most important ones. The COVID-19 classification model has been adapted to accommodate the feature selection approach. To perform this research, the researchers used data from 1495 infected patients and 1027 patients with community acquired pneumonia from the COVID-19 CT scan dataset (CAP). Their approach has attained an accuracy rate of 91,79 percent, a sensitivity score of 93,05 percent, a specificity score of 89,95 percent and lastly and AUC of 96,35 percent.

The accessibility of a wide and diverse, and large set of data, including radiological images is vital for the representativeness and predictive capability of models based on neural networks. Nevertheless, in practise, there is frequently a shortage in the appropriate data in certain sectors. Another study by [12] tries to overcome this challenge by providing synthetic data of X-Ray scans of COVID-19 positive and negative individuals. The authors depended on generative models to provide X-Ray images. Adding synthetic data to a VGG16 classifier improves the assessment metrics significantly, according to the study team. The accuracy and F1 score both increased to 0,95 and 0,94, respectively, from 0,85 and 0,84.

Spike response model (SRM) neurons with excellent computation capabilities have been proposed by the researchers in this study [13]. Using the built network, they encoded pictures and employed frequency spike encoding to represent data. The pictures were processed in a manner similar to that utilised by the first layers of the brain's visual cortex. Finally, major characteristics were extracted from the network's output and utilised to further enhance categorization. Grayscale pictures having noise or partly unclear image samples were effectively learned and categorized by the model twenty times faster and with a classification ratio equivalent to that of conventional SRM models, as stated by the authors.

Chapter 3

Problem and Model Description

3.1 Problem Description

As previously demonstrated, the purpose of this research paper is to build a classification model to classify COVID-19 positive/negative classes based on different SNN potential update rules. The potential based features used in the classifier are extracted from a DCSNN, built with a specific structure, and the corresponding proposed ME-IF neuron model. An SNN's basic building element is the neuron, and the input, hidden, and output layers are made up of multiple connected neurons. The neuron's membrane has a resting potential when it is not stimulated. The membrane potential increases or decreases with each input spike from interconnected neurons. When the potential reaches a certain level (threshold), the neuron enters a refractory phase during which no additional input is permitted and the potential stays unchanged. In the basic IF neuron model, the membrane potential at each timestep t is updated accordingly as shown in eq. (1):

$$V_i(t) = V_i(t - 1) + \Sigma_j(W_{j,i}\, S_j\, (t - 1)) \quad (1)$$

Where $V_i(t)$ is the membrane potential at timestep t of the ith neuron in the convolutional layer, $W_{j,i}$ is the synaptic weights matrix of between the ith neuron in the convolutional layer, and the jth presynaptic neuron.

3.2 Modified Exponential IF Neuron Model

Based on data from neuroscientific research, a variety of neuron models have been proposed with differing extents of biological validity [14]. Those models are based on different ways of mathematically representing the neuron in the SNN, and some of them are McCulloch-Pitts model, Hodgkin-Huxley model, IF model, Izhikevich model, etc. The ME-IF model proposed in this paper has a different rule for updating the potentials in each neuron. It introduces the exponential term in the potential equation, applying simple modification in the classical IF model. The membrane potential at each timestep in the ME-IF model is represented in eq. (2) as follows:

$$V_i(t) = exp(- x)\times V_i(t - 1) + (1 - exp(-x)) + \Sigma_j(W_{j,i}\, S_j\, (t - 1)) \quad (2)$$

The above equation is a modified exponential integrate-and-fire neuron model that has been proposed as a potential update rule for spiking neural networks. This update rule includes a decay factor $exp(- x)$, which causes the membrane potential $V_i(t)$ of neuron i to decrease over time, as well as a constant offset $(1 - exp(-x))$, which allows the neuron to fire more frequently. The proposed equation is tested for 3 different values of x; 0,125, 1,5, and 2,5, namely ME-IF-V1, ME-IF-V2, ME-IF-V3.

Chapter 4

Data Overview

The dataset used in this research is open source and can be accessed in this GitHub Repository [15]. It includes CT chest images of individuals tested positive or negative for COVID-19. The count of positive examples in the dataset is 349, whereas the count of negative examples is 397. The CT images belong to 216 patients, that is, there are multiple images for each patient. The following two figures (Fig. 4.1, 4.2) show two data samples of positive and negative patients.

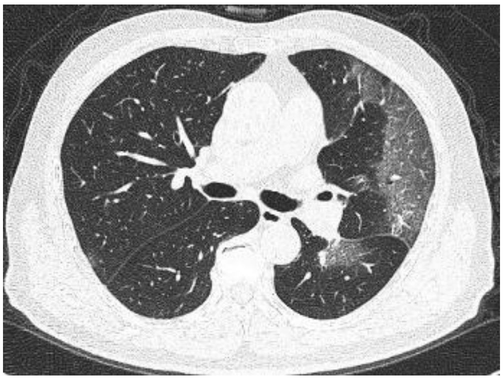

Figure 4.1: COVID -19 Positive Example

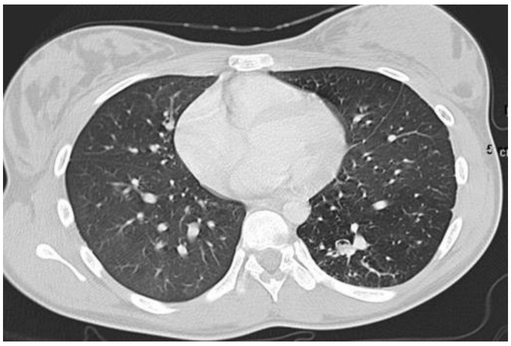

Figure 4.2: COVID-19 Negative Example

Chapter 5

Methodology

5.1 Data Preprocessing

All images are first scaled to 200×200 pixels and turned to greyscale before they can be used. Although the resizing causes considerable loss of information within images, it was necessary due to the high computational cost of SNNs. The following pipeline summarizes the rest of the data preprocessing stage. Firstly, the resized image is converted into a torch tensor, which is a is a multi-dimensional matrix that contains just one data type's elements, available in the Python's machine learning framework, PyTorch. Next, the converted tensors are processed through Gabor filters. Afterwards, lateral inhibition is applied to the filtered images to improve the overall performance of the model. Finally, the images are encoded using the intensity-to-latency encoding technique. The output of the data preprocessing stage is shown in Fig. 5.1.

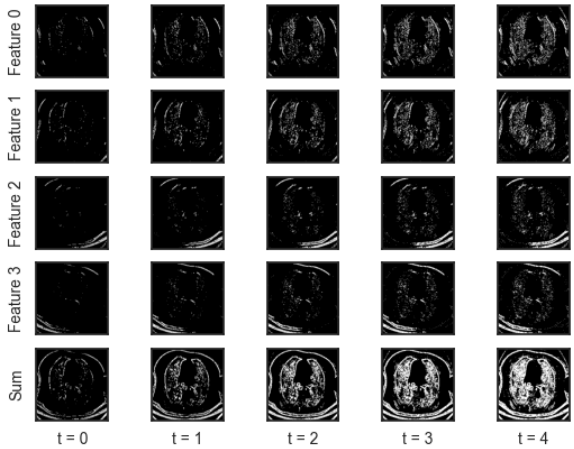

Figure 5.1: Extracted Features After Data Preprocessing

Fig. 3 shows the attributes of a single input picture following the preprocessing step. The addition of the time dimension, to account for the spiking neurons, yields the time values at the bottom. The various Gabor filters have produced the desired results, which may be seen in the various characteristics. The final feature vector is created by adding all these characteristics together. At various points in time, the traits and their summation are different. Finally, in preprocessing, the intensity-to-latency encoding is implemented.

The band-pass filter, called a Gabor filter, may be used to extract relevant characteristics from a picture. The impulsive response of these filters is produced by multiplying a Gaussian envelope function by a nonlinear oscillatory function. These basic functions assist to minimize the space-time uncertainty product, which has an immediate impact on the orientation selective behaviour of these functions when they are extended to two dimensions. SNNs have been able to better grasp membrane potentials and spiking thresholds by using the filters to extract different characteristics from pictures, both frequency-based and orientation-based data, while filtering out any noise. The Gabor filter entropy and Gabor filter energy characteristics are derived from these pictures utilising the real and imaginary components. if the edge direction is perpendicular to the Gaussian kernel wave vector, then these features work appropriately.

5.2 Deep Convolutional Spiking Neural Network

A Poisson-distributed spike is the output of the input layer, which encodes the input picture in this manner. There is a clear correlation between pixel intensity and spike creation. The intermediate stages get this new encoding. Hidden layers in feature hierarchies are built up of convolution and spatial-pooling layers placed on top of each other. Sequentially concatenated spikes are given to external supervised learning classifiers for binary categorization of incoming data. Aside from the pooling layer, all the other layers of the neural network may be trained. Adapted convolutional kernels may identify local characteristics that have spatial correlation in the input patterns using convolution, which has an inherent quality of making the network invariant to object position shifts. The pooling layers then perform a downscaling of feature maps in terms of dimension that were created by the preceding layers. Throughout the procedure, the spatial association between nearby pixels is preserved in each and every feature map. The overall archeticture of the DCSNN is shown in [8, Fig. 5.2].

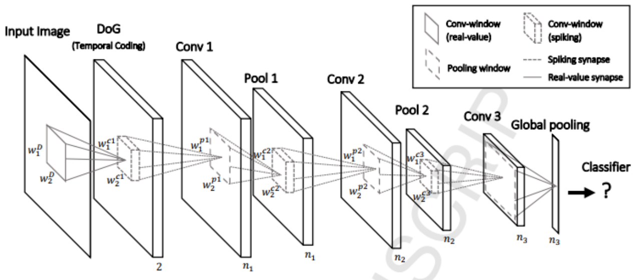

Figure 5.2: Overall DCSNN Archeticture Inspired from [8]

Each convolutional layer in the suggested structure is made up of several 2D layers of ME-IF neurons, which are essentially feature map representations. Additionally, the firing threshold is initially set to be the same for each layer's individual neurons. Using the magnitude of the synaptic weights, each ME-IF neuron's membrane potential is increased by the received spikes that fall inside its input window at each time step. These neurons don't have any leaking at all. If a neuron reaches the firing threshold, it releases a single spike and then resets until the network receives the next input picture. The kernel size used in the convolution layers was 30×30. Then the convolution is applied on a 4D input tensor of size (N, C_{in}, H, W) to produce a corresponding 4D output tensor of size (N, C_{out}, H_{out}, W_{out}), according to PyTorch documentation. In our case, N is the number of timesteps, C_{in} is the number of kernels, H is the height of the input image W is the width of the input image.

For the detection of hidden patterns in noisy spiking data, STDP has been shown to be an effective method. An unsupervised learning approach, it relies on the spike order in synapses to determine the final outcome. A synapses potentiation (pre-post) or depression (post-pre) is determined by the sequence in which presynaptic spikes and postsynaptic spikes occur, and the time differences between them. The following two rules govern weight changes: In order to raise the value of a post-synaptic neuron, it is necessary to strengthen any synapses that are involved in the firing of that neuron. Value should be reduced for synapses in which a post-synaptic neuron does not contribute to the firing of that neuron. A huge number of incoming spikes may be broken down into patterns using this technique.

Position invariability and the decrease of informational redundancies have been achieved by using pooling layers. The number of feature maps in each successive convolutional and pooling layer is equivalent to the number of extracted features in the layer before it, resulting in a one-to-one correspondence between the maps in each layer. Using the potential based SNN in this study, we have employed pooling layers with a fixed stride and a two-dimensional input window. Layers based on potential receive input from each neuron, with each neuron's output indicating the highest potential of the neurons within its window. Stride's default value is the same as the window's, but it may be changed to suit particular preferences. The whole network is run for two epochs, since there is no improvement in the overall accuracy as the number of iterations gets greater than two.

5.3 Supervised Learning

Classifiers based on deep learning perform best when a large number of training examples are available. Decisions may be made more effectively using machine learning-based classifiers when the dataset comprises smaller amounts of data [16]. A grid search algorithm was adapted to choose the best performing classifier, and the corresponding tuned hyperparameters. Accordingly, a Random Forest classifier was employed in this study as the last step in our working process to determine if the output was COVID or not, based on the retrieved features from the previous stages. After reporting the classification results, the model is built again, but with the classical IF model, and then the results are compared for both cases.

Chapter 6

Results and Discussion

6.1 Experimental Resutlts and Findings

A variety of evaluation metrics have been used to assess how well our approach, extracting features using an ME-IF based SNN, classifies COVID in CT scan images compared to the classical neuron model. The main metrics used to compare between the models were the classification accuracy score, and the f1-score. The classification accuracy rate measures how likely is it that a patient will be properly classified. The f1-score, which is also an extremely important metric in assessing the performance of any classification model, represents the recall and precesion weighted average.

First, the model with the classical IF model is run, and the classification results were recorded. The time it took the unsupervised learning to complete was approximately one minute, using CUDA 11.2. Different classifiers were tested including Random Forest classifier, XGBoost, Decision Trees, and K Nearest Neighbours. However, the Random Forest classifier was significantly better and more efficient than the rest of the classifiers. The max depth was set to eight in both cases. The following Table 6.1 shows the classification report of the model based on IF neurons.

Classical IF Model				
	precision	recall	f1-score	support
0	0,77	0,76	0,76	87
1	0,79	0,80	0,79	99
accuarcy			0,78	186
macro avg	0,78	0,78	0,78	186
weighted avg	0,78	0,78	0,78	186

Table 6.1: Classification Report of the Classical IF Model

When the DCSNN was built based on the classical IF neurons, the model showed both accuracy rate and a corresponding f1-score of 0,78. These numbers were acceptable given the amount of information loss due to image resizing. The classification error in that case was approximately 0,22. Next, the same SNN was used again to extract features from CT scans, but the three variations of the proposed ME-IF neuron model were implemented in this case. The model was built and trained using the same computational resources used in the first case and using the same parallel computing platform. The reconstructed features after the second convolutional layer are shown in Figure 6.

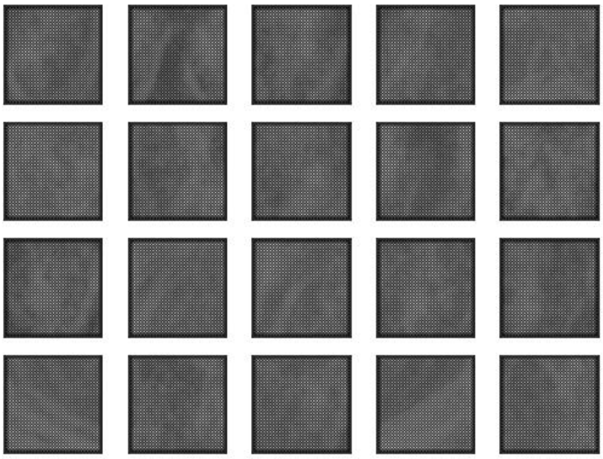

Figure 6: The Reconstructed Features After the Second Convolutional Layer

The features were reconstructed, and the figure was created using the visualization module in SpykeTorch, an open-source Python library based on PyTorch [17]. After the features were extracted in the second case, they were used to fit another random forest model. The classification report of the model based on the three versions of the ME-IF model is shown in Table 6.2.

ME-IF-V1				
	precision	recall	f1-score	support
0	0,76	0,78	0,77	87
1	0,80	0,78	0,79	99
accuarcy			0,78	186
macro avg	0,78	0,78	0,78	186
weighted avg	0,78	0,78	0,78	186
ME-IF-V2				
0	0,78	0,82	0,80	87
1	0,83	0,80	0,81	99
accuarcy			0,81	186
macro avg	0,81	0,81	0,81	186
weighted avg	0,81	0,81	0,81	186
ME-IF-V3				
0	0,73	0,79	0,76	87
1	0,80	0,75	0,77	99
accuarcy			0,77	186
macro avg	0,77	0,77	0,77	186
weighted avg	0,77	0,77	0,77	186

Table 6.2: Classification Report of the Classical IF Model

6.2 Discussion

Overall, ME-IF-V2 achieved the highest accuracy, precision, recall, and F1-score, while ME-IF-V3 had the lowest precision and recall for class 1. These findings suggest that the choice of potential update rule can have a significant impact on the performance of spiking neural networks for COVID-19 classification from CT scan images. With a singificant increase of 3% in both in the accuracy rate, and the f1-score, the ME-IF-V2 even competes with models built using larger sizes of images. Based on the aforementioned data, it can be concluded that potential-based SNN based on the suggested ME-IF-V2 model is the most effective. As opposed to DCNNs the spiking train-based SNN does not provide comparable performance, which was why potential-based SNN was employed. Table 6.3 demonstrates the difference between the accuarcies, errors, and f1-scores between the classical integrate-and-fire model and the ME-IF-V2 model.

DCSNN Neuron Model	f1-score	accuarcy	error
Classical IF model	0,78	0,78	0,22
ME-IF-V2 model	0,81	0,81	0,19

Table 6.3: A Comparison Between the Employed Neuron Models

The improved performance of this update rule could be attributed to several factors. Firstly, the decay factor helps to prevent the membrane potential of neurons from saturating and becoming unresponsive, which can occur with other types of potential update rules. Additionally, the constant offset provides a baseline level of activity that enables the neuron to respond more quickly to incoming spikes. Moreover, the ME-IF model captures more complex neuronal behavior, such as adaptation and refractoriness, that is not present in simpler models like the classical integrate-and-fire (IF) neuron model. This added complexity allows the neuron to encode information more efficiently, leading to better performance in tasks like COVID-19 classification from CT scan images. Overall, the improved performance of the ME-IF neuron model highlights the importance of selecting an appropriate potential update rule when designing spiking neural networks for specific tasks.

This study had limitations that need to be put into consideration, which include the following. The limited computational resources hindered the training and evaluation processes and prevented us from using images with sizes greater than 200×200 pixels. Additionally, the model’s algorithm included some for loops which might have increased the training time. The model should also be assessed and tested on different CT scans datasets, to validate its results. SNNs may be used in a variety of real-world circumstances, as shown by this study. Neuromorphic circuits' advantages also make SNNs a feasible solution for a wide range of real-world applications. A decent graphics processing unit (GPU) is often required for deep learning models in order to achieve rapid inference times. Chips are more suited for processing because of their energy efficiency and computational capacity. There is a price to pay for the benefits. Unlike deep learning models, which might take hours or days to train, they need a significant amount of time. With the right neuron model employed in an SNN, the results could be considerably better than expected.

Chapter 7

Conclusion

In conclusion, this study explored the impact of different potential update rules on the performance of Spiking Neural Networks (SNNs) for COVID-19 classification from CT scan images. Four distinct potential update rules were examined, including the classical IF and several variants of a ME-IF model. Results showed that the proposed ME-IF-V2 neuron model with an exponential decay constant of -1,5 achieved better performance compared to other models. The developed SNN-based model successfully classified COVID and non-COVID chest CT scan images with an accuracy and F1 score of 0,84. These findings demonstrate the potential of SNNs and neuromorphic computing in medical image analysis and disease diagnosis, particularly for detecting COVID-19 early on and stopping its spread. Further research can explore the application of SNNs in other medical imaging modalities and investigate the impact of other potential update rules on SNN performance.

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