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Chapter 1

Introduction

1.1 Motivation

Brain tumors pose a significant challenge in modern healthcare, with early and accurate diagnosis being crucial for effective treatment and improved patient outcomes. Traditional medical image analysis methods, such as convolutional neural networks (CNNs), have demonstrated strong performance but come with high computational costs, making them resource-intensive and less efficient for real-time applications.

Spiking Neural Networks (SNNs), inspired by the human brain's biological processing, offer a promising alternative. Unlike traditional artificial neural networks that rely on continuous activations, SNNs process information using discrete spikes, leading to potential improvements in power efficiency, computational efficiency, and real-time processing. This project is motivated by the potential of SNNs to overcome the limitations of CNN-based tumor segmentation by providing an energy-efficient, biologically plausible solution for medical imaging. By leveraging Convolutional Spiking Neural Networks (CSNNs) with spike-based visual attention, this research aims to develop a more accurate and computationally efficient method for brain tumor localization and segmentation.

1.2 Problem Statement

Visual attention in medical imaging plays a crucial role in accurate diagnosis and treatment planning. However, existing methods struggle with effectively localizing tumors in a computationally efficient manner. Traditional deep learning models, such as CNNs, rely on extensive labeled data and high computational power, making them impractical for real-time and resource-constrained applications. Moreover, conventional saliency detection techniques often fail to capture biologically inspired attention mechanisms that could enhance tumor localization. This project aims to address these challenges by leveraging Spiking Neural Networks (SNNs) with a spike-based visual attention mechanism for tumor localization in medical images. Inspired by the human brain's efficiency in processing visual information, SNNs offer significant advantages in power efficiency and biologically plausible feature extraction, potentially leading to more accurate and computationally feasible medical image analysis.

1.3 Objectives

The objectives of this work are:

- Create a CSNN model with Visual Attention Mechanism
- Train and Test the model on Brain Tumor dataset results in Saliency Maps.
- Compare the performance of the SNN Model aganist other CNN Models from previous works

1.4 Thesis Outline

In this thesis, we propose a Spiking Neural Network (SNN) model with a spike-based visual attention mechanism for efficient and accurate tumor localization in medical images. Chapter 1 introduces the motivation, problem statement, and overall structure of the thesis. Chapter 2 provides an in-depth explanation of the key concepts and technologies used, including an overview of traditional and SNN-based approaches for visual attention in medical imaging, along with a summary of relevant previous work. Chapter 3 details the development of our proposed model, including dataset preprocessing, model architecture, and training methodology. Chapter 5 presents and analyzes the results, comparing our approach to conventional deep learning models. Finally, Chapter 5 concludes the thesis, discussing key findings and potential future research directions to further enhance SNN-based visual attention mechanisms in medical imaging.

- **Concept Overview:** A brief explanation of most concepts and technologies used throughout this paper.
- **Literature Review:** A compilation of all previous work done in the past regarding the implemented project or any of the technologies and methodologies used.
- **Methodology:** Workflow overview on how the project was implemented and how the environment developed could be replicated.
- **Results:** The section is split into to parts the first part compares between datasets tried and the second part is the results received from the project.
- **Conclusion:** A brief discussion of what was achieved in this paper, and the future work that could be done to excel the results and further development.

Chapter 2

Background

2.1 Concepts Overview

This section provides an overview explanation of all the technologies utilized in our methodology, offering a description of the fundamental concepts and tools.

2.1.1 Deep Learning

Deep Learning is one of the most emerging techniques in the modern era, as illustrated in Figure 2.1.

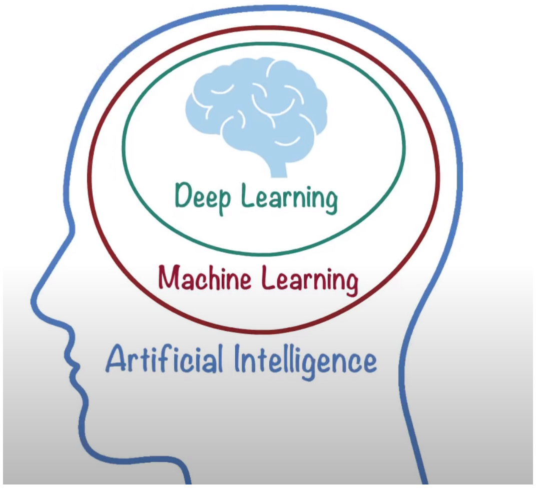


Figure 2.1: Deep Learning as a Subset

Deep learning is a subfield of machine learning that focuses on training artificial neural networks with multiple layers to extract hierarchical features from raw data. These deep networks have revolutionized various domains, including image recognition, natural language processing, and medical diagnostics, by achieving state-of-the-art performance through large-scale datasets and high computational power.

The learning process in deep learning consists of two primary phases: forward propagation and backpropagation. In forward propagation, the input data is passed through multiple layers of neurons, where each neuron applies a linear transformation followed by a non-linear activation function. Initially, the network starts with randomly assigned weights and biases, which determine how information flows from the input layer to the hidden layers and finally to the output layer. The number of neurons in the input layer is dependent on the dimensionality of the dataset.

Backpropagation is a crucial step in deep learning, as it allows the network to adjust its parameters based on the error observed in the predictions. Using a loss function, which quantifies the deviation between predicted and actual values, the network computes gradients with respect to each weight through gradient descent. The weights are then updated in the opposite direction of the gradient to minimize the loss. Several types of activation functions influence this learning process, such as the sigmoid function, which is useful for binary classification but suffers from the vanishing gradient problem, and the ReLU function, which mitigates this issue but can lead to the dying ReLU problem, where neurons become inactive. Other activation functions, such as tanh, Leaky ReLU, and step functions, are also used based on task requirements.

Loss functions play a key role in training deep networks by measuring the error of predictions. Different tasks require different loss functions; for regression problems, squared error and Huber loss are commonly used, while classification tasks utilize binary cross-entropy for binary classification and multi-class cross-entropy for multi-class problems. Advanced loss functions, such as hinge loss for support vector machines and Kullback-Leibler divergence for probabilistic models, further refine model accuracy.

To optimize deep networks efficiently, various optimization algorithms are used. Gradient descent aims to minimize the loss function by iteratively updating the weights based on computed gradients. However, choosing an appropriate learning rate is essential to prevent the model from getting stuck in local minima. Stochastic Gradient Descent (SGD) improves this by using small subsets of training data (batches) per iteration, allowing for faster convergence and reduced memory consumption. Optimizers such as Adagrad, RMSprop, and Adam introduce adaptive learning rate strategies to improve convergence speed and stability. While Adagrad assigns different learning rates per feature, making it effective for sparse datasets, RMSprop maintains a moving average of gradients to prevent diminishing learning rates. Adam combines both momentum and adaptive learning rates, making it one of the most widely used optimizers in deep learning.

In addition to optimization techniques, the concept of hyperparameters and model parameters is essential in deep learning. Model parameters, such as weights and biases, are learned from data, whereas hyperparameters, such as learning rate, batch size, and the number of epochs, are predefined and tuned to improve model performance. An epoch represents one complete pass of the entire dataset through the network, while batch size determines the number of training samples processed before updating weights. Multiple epochs help the model generalize, but excessive training can lead to overfitting.

Deep learning techniques can be categorized into different learning paradigms: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning trains models on labeled data to perform classification and regression tasks. Classification algorithms, such as support vector machines, k-nearest neighbors, and random forests, assign data points to predefined categories, whereas regression models, such as linear regression and multivariate regression, predict continuous values. Unsupervised learning, on the other hand, discovers hidden patterns in unlabeled data using clustering techniques like k-means and hierarchical clustering. Association rule learning identifies relationships between different entities, making it useful for recommendation systems. Reinforcement learning enables models to learn from interaction with an environment by maximizing rewards through exploration and exploitation strategies.

To prevent overfitting, deep learning models employ regularization techniques such as dropout, dataset augmentation, and early stopping. Dropout randomly removes neurons during training to prevent reliance on specific features, while dataset augmentation artificially increases training data by applying transformations. Early stopping monitors validation error and halts training when performance begins to degrade.

Deep neural network architectures vary depending on application requirements. Fully connected feedforward neural networks are the most basic, passing data sequentially from input to output layers. Convolutional Neural Networks (CNNs) introduce convolutional layers that extract spatial hierarchies in images, followed by pooling layers that reduce dimensionality while preserving important features. Recurrent Neural Networks (RNNs) and their advanced variants, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Neural Networks (GRNNs), capture sequential dependencies in time-series data. Normalization techniques are also employed to stabilize training, while Spiking Neural Networks (SNNs) bring biological plausibility to deep learning by mimicking the behavior of real neurons through discrete spikes.

By leveraging these theoretical concepts and architectural advancements, deep learning continues to push the boundaries of artificial intelligence, offering powerful solutions across a wide range of applications.

2.1.2 Image Segmentation

Image segmentation is a fundamental task in computer vision that involves partitioning an image into meaningful regions to facilitate analysis. This technique is widely used in medical imaging, autonomous driving, and object detection. Traditional segmentation methods rely on thresholding and clustering, while deep learning-based approaches, such as U-Net [1], have revolutionized the field. Attention-based segmentation models further enhance accuracy by dynamically focusing on the most relevant regions [3].

2.1.3 Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of biological neural networks. They consist of interconnected layers of artificial neurons that process information in a hierarchical manner. Each neuron applies a weighted sum to its inputs, followed by a non-linear activation function, enabling ANNs to learn complex patterns. Deep ANNs, commonly used in deep learning applications, have demonstrated remarkable success in image processing, natural language processing, and reinforcement learning tasks [4].

2.1.4 Spiking Neural Networks

Spiking Neural Networks (SNNs) represent a biologically plausible approach to neural computation, where neurons communicate using discrete spikes rather than continuous activations. This event-driven nature makes SNNs highly energy-efficient compared to traditional deep learning models. Training SNNs is challenging due to their non-differentiability; however, recent advancements, such as spike-based backpropagation [5] and surrogate gradient methods, have improved their performance. SNNs have found applications in robotics, neuromorphic computing, and real-time signal processing [6].

2.1.5 Visual Attention

Visual attention mechanisms play a crucial role in enhancing deep learning models by selectively focusing on important features while suppressing irrelevant information. In deep learning, attention mechanisms, such as self-attention and spatial-channel attention [2], have significantly improved the performance of image classification, object detection, and image segmentation models. In SNNs, attention-based architectures enhance spike processing efficiency, leading to state-of-the-art accuracy in vision tasks [7].

2.2 Literature Review

2.2.1 Advancements in Spiking Neural Networks

Spiking Neural Networks (SNNs) have emerged as a promising alternative to traditional Artificial Neural Networks (ANNs) due to their bio-inspired architecture and event-driven nature. The development of SNN originates from the Hebb rule and the Hodgkin-Huxley model in Fig 2.2 from 1950s to 2020s with Neuromorphic vision sensors and designs.

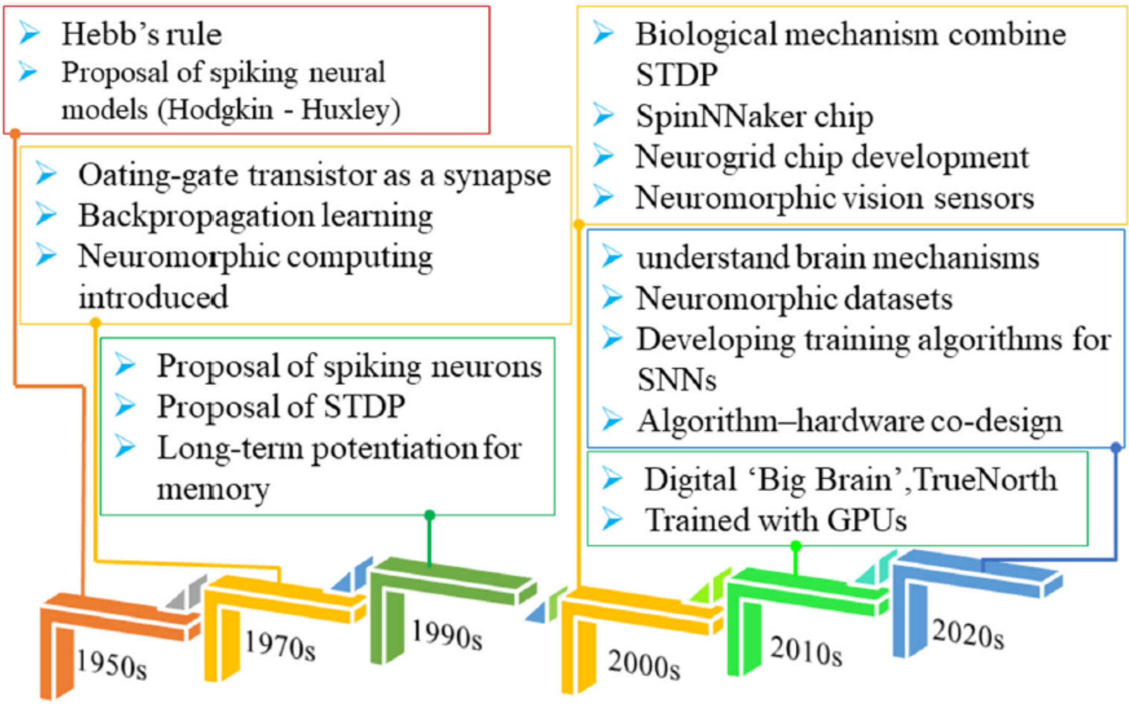


Figure 2.2: Development history of SNN

Unlike conventional deep learning models that rely on continuous-valued activations, SNNs operate using discrete spikes, closely resembling the functioning of biological neurons. This unique property allows for efficient temporal processing and energy-efficient computations, making SNNs suitable for neuromorphic computing platforms. In the work of Niu et al. [6] shows the latest concepts and mechanisms of the spiking neurons. As shown in Fig 2.3 the spiking neuron model is to equivalent neurons to RC circuits and simulate neurons through capacitance C and resistance R. SNNs also were shown to achieve competitive accuracy with significantly lower power consumption when implemented on neuromorphic hardware.

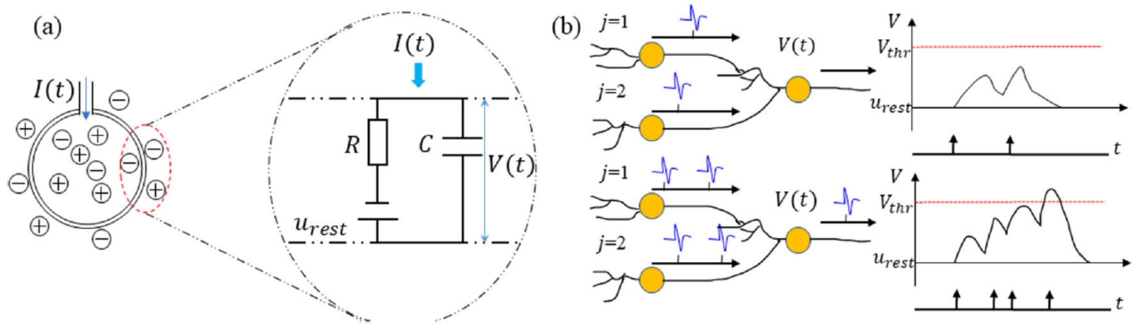
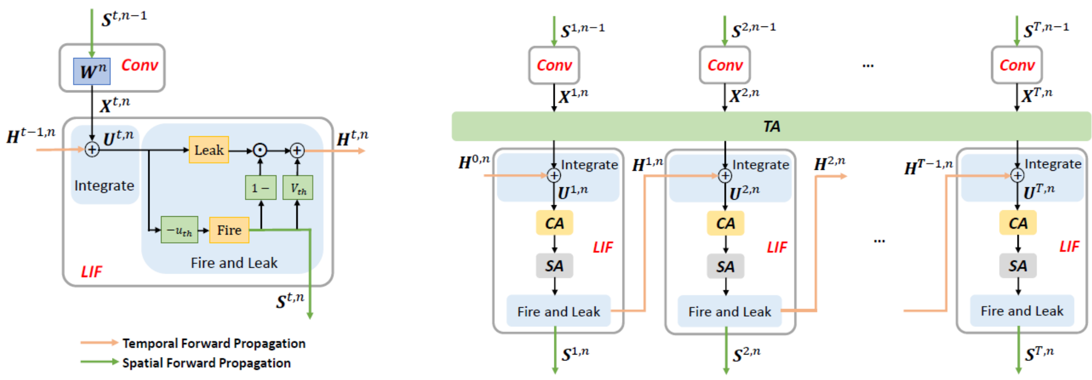


Figure 2.3: (a) The equivalent model of biological neurons. (b) The membrane potential accumulation and spike emission of spiking neurons

Early research in SNNs focused on understanding the dynamics of spiking neurons and their potential for machine learning applications with various neuron models, such as the Leaky Integrate-and-Fire (LIF) and Hodgkin–Huxley models, have been explored to simulate biological neural behavior by Tavanae et al. [4]. More recent works have extended these models to deep SNN architectures, enabling complex tasks such as image recognition, pattern detection, and medical image segmentation. Lee et al. [5] demonstrated how the integration of residual connections in deep SNNs significantly improves convergence and training stability. Advances in training techniques, including ANN-to-SNN conversion which is used by Patel et al. [8], surrogate gradient methods, and evolutionary optimization algorithms, have further improved the performance of deep SNNs.

2.2.2 Attention Mechanisms in SNNs

Attention mechanisms have significantly enhanced the performance of deep learning models, and their integration into SNNs has led to notable improvements in information processing. Inspired by the selective focus of biological neural systems, attention modules in SNNs optimize spike activity by dynamically modulating synaptic weights and membrane potentials across different dimensions. Yao et al. [2] proposed a multi-scale attention mechanism that enhances feature extraction efficiency in spiking architectures shown in Fig 2.4.



(a) Conv-based LIF-SNN layer (b) Multi-dimensional attention SNN

Figure 2.4: Multi-dimensional attention SNN

Multi-dimensional attention frameworks have been proposed to regulate spike flow at temporal, spatial, and channel levels, allowing SNNs to selectively emphasize relevant input features while suppressing redundant information. Studies have demonstrated that attention-enhanced SNNs outperform conventional SNNs in large-scale classification tasks. In this paper Cai et al. [7], mechanisms as SCTFA-SNN not only improve accuracy but also enhance the energy efficiency of SNN architectures making them more practical for deployment on neuromorphic hardware.

2.2.3 Spiking Neural Networks in Medical Imaging

The application of SNNs in medical image analysis has gained momentum due to their ability to process sparse, event-driven data efficiently. Unlike conventional deep learning models that require extensive labeled datasets and high computational resources, SNNs leverage temporal encoding schemes to extract meaningful and important patterns from medical images with minimal power consumption. Fu and Dong [9] introduced a reservoir SNN-based method for breast cancer detection showing in Fig 2.5 using Readout neurons use the ReSuMe algorithm for training, and the Fruit Fly Optimization Algorithm (FOA) is employed to optimize the network architecture achieving high accuracy with lower energy requirements compared to traditional CNN-based approaches.

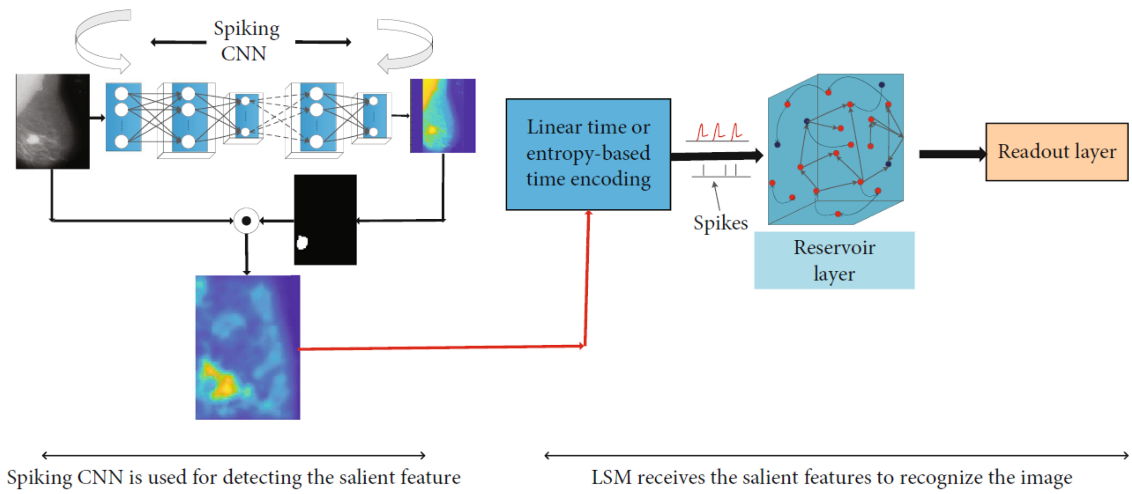


Figure 2.5: Schematic diagram of the proposed methods

Saliency-based SNNs have been developed for lesion detection and tumor classification in modalities such as MRI, ultrasound, and mammography. These networks utilize biologically inspired feature extraction techniques, where spiking convolutional layers detect critical regions of interest while preserving temporal information. Takács and Manno-Kovacs [10] demonstrated the effectiveness of combining saliency features and integrating contour detection Chan-Vase method shown in Fig 2.6 with deep learning models for improved segmentation accuracy in MRI-based tumor detection.

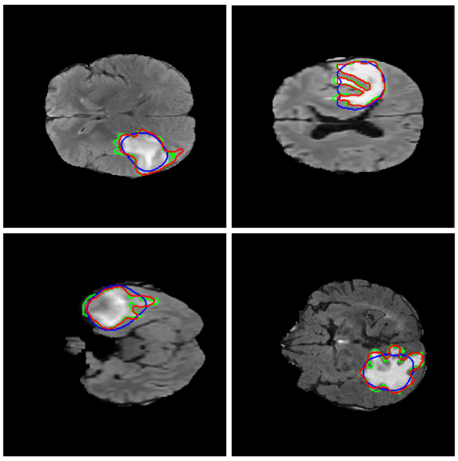


Figure 2.6: Tumor contour detection using the Chan-Vese method; blue is the thresholded, binary tumor estimation of the color-spatial saliency map, red is the improved result of the active contour step, green is the ground truth tumor outline

Recent research has demonstrated the effectiveness of SNNs in action recognition, gesture classification, and robotic perception tasks using event-based imaging. The integration of spiking neural architectures with neuromorphic processors has further enhanced the feasibility of deploying event-driven AI systems in mobile and embedded applications [11].

2.2.4 Spiking Convolutional Neural Networks (SCNNs)

Spiking Convolutional Neural Networks (SCNNs) combine the strengths of SNNs with convolutional architectures, enabling efficient feature extraction while maintaining biologically inspired spike-based processing. Unlike traditional CNNs, which rely on continuous-valued activations, SCNNs process data using discrete spike events, allowing for reduced energy consumption and improved temporal feature encoding [8].

Recent studies have demonstrated the effectiveness of SCNNs in computer vision tasks such as object detection and scene segmentation. Researchers have integrated SCNNs with attention mechanisms to improve feature selection and achieve competitive accuracy in real-world applications [12]. Additionally, hybrid ANN-SCNN models have been developed to leverage the advantages of both paradigms, optimizing performance while retaining the efficiency benefits of spike-based computation.

2.2.5 SNNs for Image Processing, Segmentation and Classification

SNNs have been widely applied in image classification tasks due to their ability to efficiently encode spatial and temporal information. In the work of Patel et al. [8], a converted SNN-based model demonstrated competitive performance on standard image classification datasets while consuming significantly less power than traditional deep learning models using a modified version of the ISBI 2D EM Segmentation dataset consisting of microscope images of cells shown in Fig 2.7.

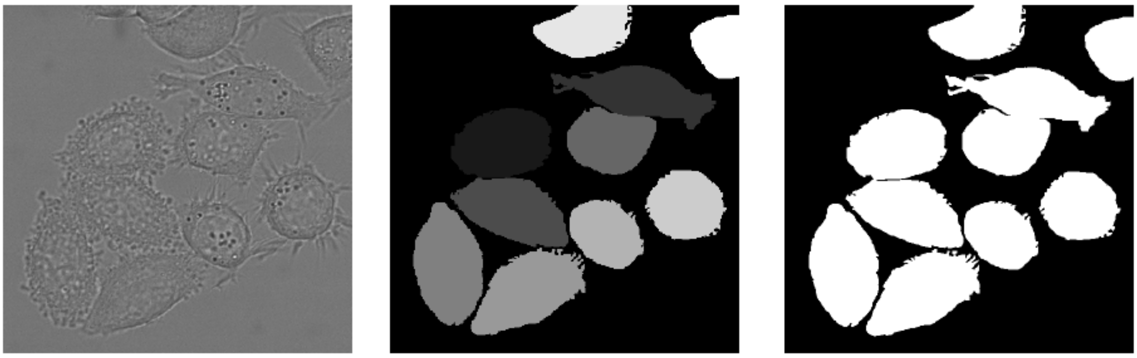


Figure 2.7: Example from the original ISBI cell dataset shows Input image, Ground truth with distinct classes for individual cells and Ground truth with two classes

Researchers have explored different spike encoding techniques, such as rate coding and temporal coding, to optimize SNNs for image processing. Rate-based encoding represents pixel intensity using spike frequency, while temporal coding leverages spike timing to convey information more efficiently [13]. These techniques have been instrumental in adapting SNNs for high-resolution image recognition and real-time vision applications.

2.2.6 Neural Network Architectures

The evolution of SNN architectures has led to the development of several novel frameworks tailored for specific tasks. From simple feedforward SNNs to deep spiking residual networks, researchers have continually refined network designs to balance biological plausibility and computational efficiency [1].

One major advancement is the introduction of hybrid neural architectures, which combine conventional deep learning layers with spiking neuron models. These architectures leverage the representational power of ANNs while maintaining the efficiency benefits of SNNs. Furthermore, the use of biologically inspired mechanisms such as lateral inhibition and recurrent connectivity has enhanced the capabilities of modern SNN frameworks [3].

Neural network architectures have evolved significantly, leading to the development of specialized models for various applications. Among the most influential architectures are U-Net and ResNet, both of which have been adapted for use with SNNs.

U-Net, initially introduced for biomedical image segmentation, utilizes an encoder-decoder structure to enhance feature extraction and localization by Ronneberger et al. [1]. The contracting path captures contextual information, while the expanding path enables precise segmentation. Attention-based variants of U-Net, such as Attention U-Net [3], have further improved performance by incorporating spatial attention mechanisms that highlight crucial image regions.

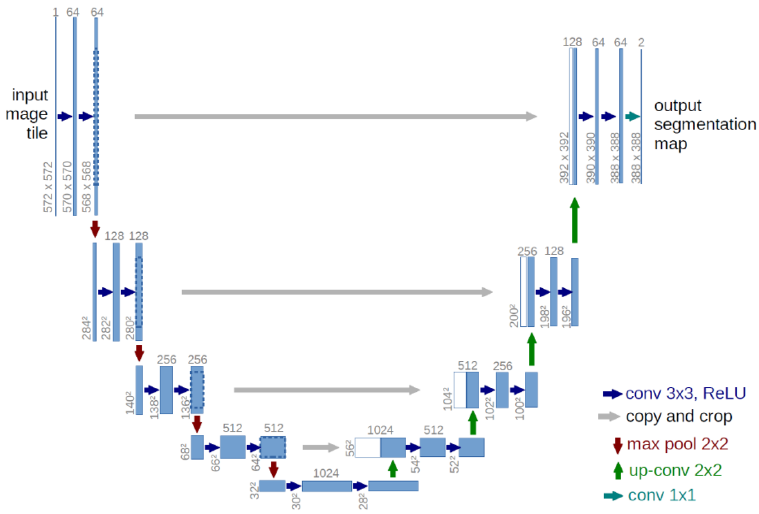


Figure 2.8: Original U-Net architecture for semantic segmentation [1]

ResNet, or Residual Networks, introduced the concept of skip connections to address the vanishing gradient problem in deep architectures. This structure enables more effective training of very deep networks by allowing gradients to flow directly through shortcut connections. Researchers have successfully implemented ResNet-like architectures in SNNs, improving convergence and maintaining stability during training [5].

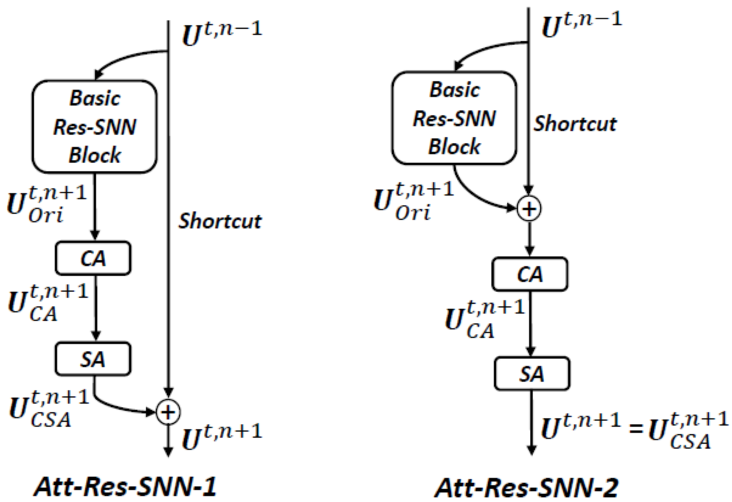


Figure 2.9: Attention residual block contains three parts: basic Res-SNN block, shortcut, and CSA module. We exploit MA on the basic Res-SNN block outputs (i.e., membrane potential of spiking neurons) in each block [2].

The integration of these architectures with SNNs has enhanced their applicability in tasks such as medical imaging, object recognition, and autonomous navigation. Future research continues to explore hybrid models that combine the advantages of both

ANN and SNN frameworks to achieve superior performance while leveraging the energy efficiency of spike-based computations.

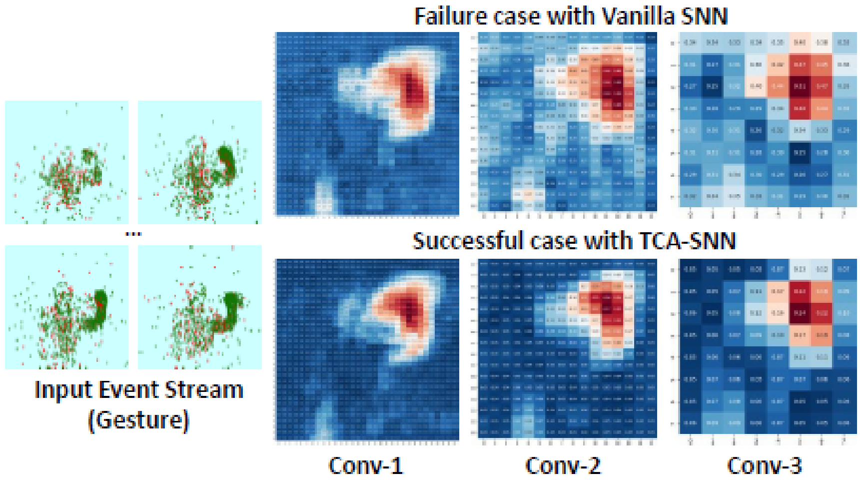
2.2.7 Training Techniques and Hardware Optimization

One of the key challenges in deploying deep SNNs is their training complexity, primarily due to the non-differentiability of spike-based activation functions. Several techniques have been proposed to address this issue, including surrogate gradient methods, temporal backpropagation, and biologically inspired plasticity rules [4].

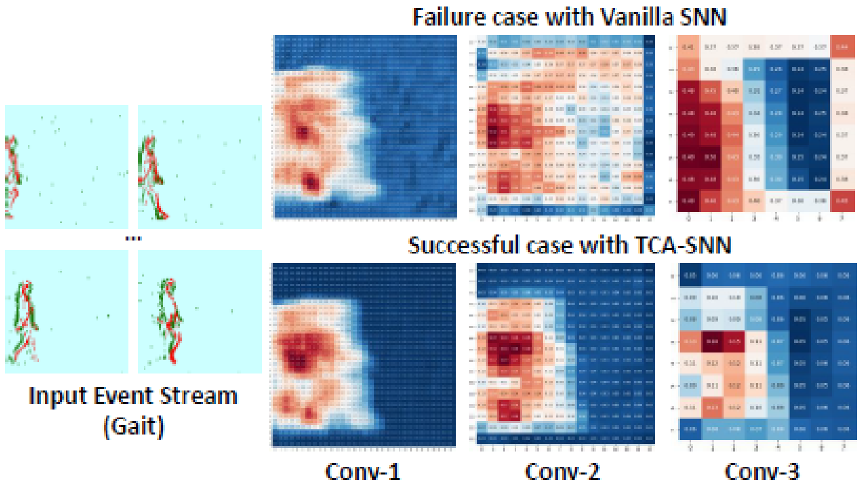
Efforts have also been made to optimize SNNs for neuromorphic hardware, reducing power consumption while maintaining accuracy. Lee et al. [5] proposed spike-based backpropagation techniques that enable efficient training of deep spiking networks. Additionally, hardware-aware training techniques, including quantized weight updates and sparsity-driven learning algorithms, have been introduced to enhance the efficiency of SNN deployment on edge devices.

2.2.8 Event-Based Vision and Neuromorphic Computing

Event-based vision systems, powered by dynamic vision sensors (DVS), have emerged as a natural application domain for SNNs. Unlike conventional frame-based cameras, DVS sensors capture visual data in an asynchronous manner, generating spikes in response to changes in brightness. This event-driven representation is inherently compatible with SNNs, allowing for efficient processing of real-time video streams with minimal latency [14].



(a) Case study on DVS128 Gesture



(b) Case study on DVS128 Gait

Figure 2.10: Case study on event-based tasks. We can observe that attention drives SNNs to focus on the target while the vanilla model shows more decentralized spiking activations [2]

Chapter 3

Methodology

3.1 Capturing video and cutting into frames

The first step is to

3.2 Face detection

Face detection was done

3.3 Face Pre-processing

The faces could not be passed to a neural network as red, green and blue channels

As shown in figure 3.1 the difference between RGB and LBP images is huge, the LBP highlights more distinct features in the face like the mouth, eyes and edges more than the RGB image does. After this process the faces distinct feature are much more detectable and the image is ready to be passed to the neural network.

Figure 3.1: Conversion from RGB to LBP

Chapter 4

Results

4.1 Experiment setting and Dataset

4.1.1 Tools used

The programming language

4.1.2 Dataset

Datasets have been developed by multiple companies, universities and even individuals have been very promising.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

In this paper we discuss some techniques of Deep Learning to determine the Age of a humans based on their facial features.

5.2 Future Work

This project is missing some hardware work using Raspberry Pi and a video surveillance camera.

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