Summary

This thesis investigates neuromorphic computing from multiple perspectives, including bio-inspired algorithms, specialized hardware accelerators, optimization techniques, and continual learning strategies. By drawing inspiration from biological processes, this research aims to enhance the efficiency of Artificial Intelligence (AI) in edge computing, facilitating the development of autonomous and real-time intelligent systems. AI has already revolutionized various industries, including healthcare, autonomous systems, manufacturing, space exploration, and sustainable energy, by leveraging large datasets, pattern recognition, and intelligent decision-making. However, the increasing complexity of AI models presents significant computational challenges, particularly in terms of energy efficiency and real-time processing. Traditional AI systems primarily rely on cloud computing, which, despite its computational power, introduces latency and privacy concerns, making it unsuitable for real-time and security-sensitive applications. Edge AI addresses these limitations by enabling local execution on resource-constrained devices such as IoT sensors, embedded systems, and autonomous machines. Nonetheless, deploying AI at the edge is constrained by limited power, memory, and computational capacity, necessitating innovative solutions to improve efficiency. To optimize AI for edge applications, several techniques have been developed. Among these, neuromorphic computing offers one of the most promising approaches by mimicking the brain's event-driven processing and distributed memory mechanisms. This biologically inspired paradigm enables highly efficient AI models that operate with minimal energy consumption. The contributions of this thesis to neuromorphic engineering and Spiking Neural Network (SNN) research span multiple areas. A primary focus is the development of specialized hardware accelerators to enhance SNN execution. This includes a high-level Python framework designed to simplify the design, training, and deployment of Field Programmable Gate Array (FPGA)-based SNNs, making these technologies more accessible to researchers without extensive hardware expertise. Additionally, this work explores automatic optimization techniques for SNN architectures, leveraging multi-objective optimization strategies to balance accuracy, power efficiency, and latency. Another key aspect is continual learning in SNNs, allowing models to dynamically adapt and refine their knowledge as they process new data, thereby replicating the flexibility of biological learning.

Furthermore, this research investigates emerging technologies and analog circuits to significantly reduce power consumption in healthcare applications. By integrating biological inspiration with computational efficiency, this work advances the field of edge AI through neuromorphic principles, hardware acceleration, and optimization techniques. The ultimate goal is to enable the development of more energy-efficient, adaptive, and autonomous AI systems, providing scalable solutions to real-world challenges in intelligent computing.