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Real - Time Emotion Recognition using Spiking Neural Networks on Wearable Edge Devices

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ABSTRACT: Real-time emotion recognition through facial expressions offers significant potential for improving human-computer interactions and personalizing user experiences. This research introduces a novel approach using Spiking Neural Networks (SNN) on wearable edge devices to achieve this. The approach incorporates key technologies like Open Neural Network Exchange (ONNX), Message Queuing Telemetry Transport (MQTT), and Long Short-Term Memory (LSTM) networks to boost the efficiency and accuracy of emotion recognition systems in real-world scenarios. ONNX enables seamless model interchange and deployment across various hardware platforms, ensuring scalability and flexibility. The optimized model conversion for wearable edge devices enhances interoperability and efficiency in real-time emotion recognition. MQTT acts as a lightweight, reliable protocol for smooth data exchange between wearable devices and external systems, facilitating real-time transmission of facial expression data and inference results. This setup supports collaborative processing and decision-making across distributed networks, improving system responsiveness and scalability. Additionally, the use of LSTM networks helps capture temporal dependencies in facial expressions, enhancing the accuracy and robustness of emotion recognition systems by effectively modeling sequential data and long-term dependencies.

KEYWORDS: Spiking Neural Networks (SNNs), Open Neural Network Exchange (ONNX), Long Short-Term Memory (LSTM), and Message Queuing Telemetry Transport (MQTT)

I. INTRODUCTION

Emotion recognition from facial expressions is an intriguing area with applications ranging from human-computer interaction to mental health monitoring .With the advent of wearable technology and the increasing need for real-time processing, there is a growing interest in using advanced neural network architectures, such as SNNs, to perform emotion recognition tasks directly on wearable edge devices .This integration holds the potential to enhance both accuracy and efficiency, providing seamless and personalized user experiences across various domains. The use of Field Programmable Gate Arrays (FPGA) and Application-Specific Integrated Circuits (ASIC) play a crucial role in enhancing the performance and efficiency of real-time emotion recognition systems based on SNN .These hardware platforms provide customizable and parallel processing capabilities, making them ideal for implementing complex neural network architectures optimized for low-latency inference on edge devices. By utilizing the inherent parallelism and reconfigure ability of FPGA and the specialized hardware design of ASIC, researchers and developers can create and deploy efficient SNN-based emotion recognition systems that meet the stringent requirements of real-time processing. Additionally, the adoption of standardized formats like ONNX enables seamless model deployment and interoperability across various hardware platforms and software frameworks. ONNX facilitates the conversion and exchange of trained neural network models between different deep learning frameworks, allowing developers to leverage pre-trained models and optimize them for deployment on FPGA and ASIC-based edge devices.

The protocols such as MQTT are essential for enabling seamless interaction between wearable edge devices and protocols such as MQTT are essential for facilitating seamless interaction between wearable edge devices and external systems. MQTT provides lightweight and reliable messaging communication suited for resource-constrained environments, enabling real-time data exchange between edge devices and cloud servers or other edge devices. By using MQTT for data transmission, SNN-based emotion recognition systems can integrate smoothly with existing infrastructure and enable collaborative processing and decision-making across distributed networks. Additionally, advanced neural network architectures such as LSTM and Temporal Convolutional Neural Networks (TCNN) offer complementary capabilities for capturing temporal dependencies and spatial features in facial expressions, improving the accuracy and robustness of emotion recognition systems. LSTM networks are adept at modeling sequential data and capturing long-term dependencies, making them suitable for analysing temporal patterns in facial expressions over

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time. Conversely, TCNNs use convolutional operations to extract spatial features from input data, facilitating efficient and scalable processing of high-dimensional image data. In this context, SNNs present a promising paradigm for real-time emotion recognition from facial expressions on wearable edge devices. SNNs replicate the asynchronous and event-driven processing found in biological neural networks, allowing for efficient computation and communication of spatiotemporal information inherent in facial expressions. By harnessing the inherent parallelism and sparsely of spike-based processing, SNNs have the potential to achieve high accuracy and energy efficiency in real-time emotion recognition tasks, making them well-suited for deployment on resource-constrained edge devices.

The objectives are:

- Develop a real-time emotion recognition system capable of accurately analyzing facial expressions.
- Utilize SNNs to achieve efficient processing of spatiotemporal information inherent in facial expressions.
- Implement the system on wearable edge devices equipped with FPGA and ASIC to optimize performance.
- Explore the interoperability of neural network models using ONNX to enable seamless deployment across various hardware platforms.
- Investigate efficient communication protocols like MQTT for data exchange between wearable edge devices and external systems.

II. LITERATURE WORK

Research on real-time emotion recognition from facial expressions using SNNs on wearable edge devices has gained significant attention recently due to its potential to transform human-computer interaction and enhance user experience. Several studies have examined the feasibility and effectiveness of employing SNNs for emotion recognition tasks, utilizing the processing capabilities of wearable edge devices to achieve low-latency and energy-efficient solutions. A key advantage of using SNNs for real-time emotion recognition is their ability to mimic biological neuronal behaviour .allowing for efficient processing of the spatiotemporal information inherent in facial expressions. This bio-inspired approach holds promise for achieving high accuracy and robustness in emotion recognition, even in dynamic and noisy environments typically found in real-world applications. Furthermore, deploying SNNs on wearable edge devices offers the benefit of localized processing, reducing the need for data transmission to centralized servers and thereby enhancing privacy and security. By performing inference tasks directly on the device, SNN-based emotion recognition systems can operate in real time without relying on continuous network connectivity, making them suitable for use in remote or resource-constrained environments. However, despite these benefits, several challenges and limitations exist in implementing real-time emotion recognition using SNNs on wearable edge devices. One significant drawback is the computational complexity associated with training and inference tasks, which may constrain the hardware capabilities of wearable devices and result in increased power consumption and latency. The interpretability of SNN models and the robustness of their performance across different demographic groups and environmental conditions are ongoing areas of research and development. Ensuring the reliability and fairness of SNN-based emotion recognition systems involves addressing biases in training data and optimizing model architectures for generalization to real-world scenarios. The integration of SNNs with wearable devices also introduces design considerations related to energy efficiency, memory constraints, and real-time processing requirements.

2.1 Message Queuing Telemetry Transport

The integration of MQTT aims to establish an efficient communication protocol for data transmission between edge devices and backend servers. The primary focus is on designing and implementing an MQTT-based communication framework specifically tailored for real-time emotion recognition applications on wearable edge devices. This framework will seamlessly integrate with the existing SNN-based emotion recognition pipeline, ensuring efficient data exchange and synchronization. To optimize the MQTT protocol for the application, adjustments to parameters such as quality of service levels, message size, and retention policies will be explored. The goal is to enhance data transmission efficiency, measured in terms of message latency, bandwidth utilization, and power consumption, particularly on resource-constrained wearable edge devices. Scalability and reliability are critical in edge environments, prompting an exploration of MQTT's capabilities in handling concurrent connections and ensuring message delivery reliability in dynamic edge conditions. Investigation into MQTT broker clustering techniques and fault-tolerant strategies will be conducted to improve system robustness and resilience. Security and privacy are crucial considerations when handling sensitive facial expression data. The analysis will include MQTT security mechanisms like TLS encryption, authentication, and access control to safeguard data during transmission. Additionally, privacy-preserving techniques, such as data anonymization and differential privacy, will be implemented to protect user privacy. Experimental validation will be crucial in assessing the effectiveness of the proposed integration. Real-world experiments on wearable edge devices equipped with SNN-based emotion recognition models and the MQTT-enabled communication

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framework will provide insights into performance under various conditions. These experiments will evaluate the effectiveness and efficiency of the integration, considering diverse network scenarios, user loads, and edge device configurations.

2.2 Power Consumption Calculation

Power Consumption=∑i=1L(Li×Ii)\text{Power Consumption} = \sum_{i=1}^{L} (L_i \times I_i) Power Consumption=i=1∑L(Li×Ii)

This equation estimates the total power consumption of wearable edge devices during MQTT communication by summing the product of voltage (LiL_iLi) and current (IiI_iIi) for each operating component.

2.3 QoS Adjustment

QoSadjusted=f(QoSinitial,Network Conditions)QoS_{\text{adjusted}} = f(QoS_{\text{initial}}, \text{Network Conditions})QoSadjusted=f(QoSinitial,Network Conditions)

This equation adjusts the initial Quality of Service (QoS) level based on current network conditions, such as latency, packet loss, and available bandwidth Using a function to optimize message delivery.

2.4 Long Short-Term Memory

LSTM networks, known for their effectiveness in handling sequential data processing tasks, show significant promise in various domains such as natural language processing and time series analysis. The goal is to explore how LSTM networks can enhance the accuracy and efficiency of emotion recognition systems deployed on wearable edge devices. Initial efforts will focus on acquiring and preprocessing facial expression datasets suitable for training LSTM models. This involves ensuring high data quality and eliminating noise to optimize model performance. The design and implementation of LSTM-based architectures will be carefully tailored to meet the specific needs of real-time emotion recognition tasks. These architectures will be optimized for deployment on resource-constrained wearable edge devices, with careful consideration given to memory usage, computational complexity, and power consumption.

To further improve the performance of LSTM-based emotion recognition systems, integration with existing SNNs will be pursued. This integration aims to combine the sequential processing capabilities of LSTM networks with the efficiency and scalability of SNNs. Real-time inference pipelines will be established to enable efficient emotion recognition directly on wearable edge devices, eliminating the need for continuous communication with external servers. Rigorous evaluation will be a key component of the proposed work, examining factors such as accuracy, latency, energy efficiency, and robustness under various real-world conditions. Additionally, privacy and security are critical considerations, with efforts focused on implementing privacy-preserving techniques to protect sensitive user data during emotion recognition. Furthermore, work will be done to enhance user experience by developing intuitive interfaces and personalized algorithms tailored to individual user preferences and behavioral nuances.

2.5 Inference Equations for LSTM Models

y^edge=LSTMedge(Xedge)\hat{y}_{\text{edge}} = \text{LSTM}_{\text{edge}}(X_{\text{edge}})y^edge =LSTMedge(Xedge) y^cloud=LSTMcloud(Xcloud)\hat{y}_{\text{cloud}} = \text{LSTM}_{\text{cloud}}(X_{\text{cloud}})y^cloud=LSTMcloud(Xcloud)

These equations represent the inference for LSTM models deployed on edge devices (LSTMedge\text{LSTM}_{\text{edge}}LSTMedge) and cloud servers (LSTMcloud\text{LSTM}_{\text{cloud}}LSTMcloud), where XedgeX_{\text{edge}}Xedge and XcloudX_{\text{cloud}}Xcloud are input data at the edge and cloud, respectively, and y^edge\hat{y}_{\text{edge}}y^edge and y^cloud\hat{y}_{\text{cloud}}y^cloud denote the predicted outputs.

III. GENERALIZATION CALCULATION

Generalization=1N∑i=1NL(yi,y^i)\text{Generalization} = \frac{1}{N} \sum_{i=1}^{N} L(y_i, \hat{y}_i)Generalization=N1i=1∑NL(yi,y^i)

This equation measures generalization by averaging the loss LLL over NNN samples, where yiy_iyi and y^i\hat{y}_iy^i are the actual and predicted outputs, respectively Generalization error computed as the average loss L between true labels yi and predicted labels $\hat{yi}$ across.

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Algorithm 1: LSTM-Based Emotion Recognition
Input: Facial expression dataset DDD, maximum number of training epochs MaxEpochsMaxEpochsMaxEpochs, batch size BBB, learning rate η\etaη
Output: Optimized LSTM models for edge and cloud deployment (LSTMedge\text{LSTM}_{\text{edge}}LSTMedge , LSTMcloud\text{LSTM}_{\text{cloud}}LSTMcloud)

1. Load and preprocess dataset.
2. Define and initialize LSTM architectures.
3. Initialize optimizer with learning rate η\etaη.
4. Train models with mini-batch gradient descent:
   for epoch in range(MaxEpochsMaxEpochsMaxEpochs):
   for batch in range(0, len(training data), BBB):
   Xbatch,ybatch=get_batch(training_data,batch,B)X_{\text{batch}}, y_{\text{batch}} = text{get_batch}(training_data, batch, B) Xbatch,ybatch=get_batch(training_data,batch,B) y^edge=LSTMedge(Xbatch)\hat{y}_{\text{edge}} = \text{LSTM}_{\text{edge}}(X_{\text{batch}}) y^edge =LSTMedge(Xbatch)
   Ledge=compute_loss(ybatch,y^edge)L_{\text{edge}} = \text{compute_loss}(y_{\text{batch}}, \hat{y}_{\text{edge}}) Ledge=compute_loss(ybatch,y^edge)
5. Update parameters (θ\thetaθ, LedgeL_{\text{edge}}Ledge, η\etaη)
6. Compute inference using y^edge=LSTMedge(Xedge)\hat{y}_{\text{edge}} = \text{LSTM}_{\text{edge}}(X_{\text{edge}})y^edge=LSTMedge(Xedge) and y^cloud=LSTMcloud(Xcloud)\hat{y}_{\text{cloud}} = \text{LSTM}_{\text{cloud}}(X_{\text{cloud}})y^cloud =LSTMcloud(Xcloud).
7. Calculate generalization error: Egeneralization=1N∑i=1NL(yi,y^i)E_{\text{generalization}} = \frac{1}{N} \sum_{i=1}^{N} L(y_i, \hat{y}_i)Egeneralization=N1i=1∑NL(yi,y^i)
8. Evaluate models on performance metrics.
9. Implement privacy-preserving techniques.
10. Enhance user experience with intuitive interfaces and personalized algorithms.

The algorithm aims to improve emotion detection accuracy and efficiency in wearable edge devices. It starts with acquiring and preprocessing facial expression datasets to ensure high-quality data for training. The algorithm uses LSTM networks to model and recognize emotions in real-time. Optimization techniques are applied to adapt the LSTM model for resource-constrained edge devices, focusing on reducing memory usage, computational complexity, and power consumption. Integration with Spiking Neural Networks (SNNs) enhances performance by combining LSTM's sequential processing capabilities with SNN's efficiency. Rigorous evaluation ensures the system's robustness, accuracy, and energy efficiency, while privacy-preserving techniques protect user data.

IV. OPEN NEURAL NETWORK EXCHANGE

ONNX serves as a standardized format for representing deep learning models, facilitating interoperability and optimization across various frameworks and hardware platforms. In the context of real-time emotion recognition, using ONNX can streamline model deployment and execution on wearable edge devices, improving efficiency and scalability. The first step involves converting SNN-based emotion recognition models to ONNX format to leverage these benefits.

4.1 Open Neural Network Exchange

The conversion of SNN-based emotion recognition models into the ONNX format ensures compatibility with ONNX-enabled inference engines and supports seamless deployment on wearable edge devices. This conversion process is crucial for integrating models with the lightweight and efficient runtime environment provided by ONNX, which facilitates rapid and accurate emotion recognition directly on the edge. This approach eliminates the need for continuous data transmission to centralized servers.

While the focus is on edge-based processing for real-time inference, the system also explores the integration of cloud-based resources to enhance capabilities. By leveraging ONNX's compatibility with cloud-based inference engines, the system can offload intensive computational tasks to the cloud when necessary, thereby augmenting edge-based processing with additional computational resources.

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Acknowledging the dynamic nature of emotion recognition tasks and evolving user preferences, the proposed work incorporates mechanisms for dynamic model adaptation. ONNX's flexibility supports efficient updates and modifications to deployed models, enabling continuous learning and adaptation based on user feedback and changing environmental conditions.

Privacy-preserving techniques are essential for safeguarding sensitive user data in emotion recognition systems. The proposed work integrates privacy-preserving mechanisms within the ONNX framework, ensuring that user privacy is protected during data transmission and inference processes on wearable edge devices. Rigorous evaluation is conducted to assess the performance of ONNX-enabled emotion recognition systems on wearable edge devices. Metrics such as inference latency, accuracy, and resource utilization are carefully analyzed to identify areas for optimization and improvement.

The conversion process from SNN-based emotion recognition models to ONNX format is represented by the following equation:
MONNX=∑l=1LT(MSNN(l))\mathcal{M}_{\text{ONNX}} = \sum_{l=1}^{L} T(\mathcal{M}_{\text{SNN}}(l))MONNX=l=1∑LT(MSNN(l))

This equation illustrates the process of converting the SNN-based emotion recognition model MSNN\mathcal{M}_{\text{SNN}}MSNN into the ONNX format MONNX\mathcal{M}_{\text{ONNX}}MONNX. Here, TTT denotes the transformation function applied to each layer lll of the SNN model, resulting in the corresponding layer of the ONNX model. The summation extends over all LLL layers of the SNN model, ensuring that each layer is accurately transformed and incorporated into the ONNX representation. This equation captures the iterative nature of the conversion process.

4.2 ONNX-Based Emotion Recognition

Input: SNN-based emotion recognition model MSNN\mathcal{M}_{\text{SNN}}MSNN, optimization objective OOO

Output: Optimized ONNX model MONNX-opt\mathcal{M}_{\text{ONNX-opt}}MONNX-opt

1. Convert SNN model MSNN\mathcal{M}_{\text{SNN}}MSNN to ONNX format MONNX\mathcal{M}_{\text{ONNX}}MONNX:
   a. For each layer lll in MSNN\mathcal{M}_{\text{SNN}}MSNN:
      i. MONNX(l)=T(MSNN(l))\mathcal{M}_{\text{ONNX}}(l) = T(\mathcal{M}_{\text{SNN}}(l))MONNX(l)=T(MSNN(l))
   b. Ensure ONNX model compatibility.
2. Optimize ONNX model MONNX\mathcal{M}_{\text{ONNX}}MONNX:
   a. Define optimization objective OOO.
   b. Initialize optimization algorithm.
   c. While stopping criterion not met:
      i. Evaluate ONNX model performance.
      ii. Adjust parameters to minimize OOO:
         1. MONNX-opt=argminMONNXO\mathcal{M}_{\text{ONNX-opt}} = \text{argmin}_{\mathcal{M}_{\text{ONNX}}} OMONNX-opt=argminMONNXO
      iii. Update ONNX model.
3. Deploy optimized ONNX model on edge devices:
   a. Deploy MONNX-opt\mathcal{M}_{\text{ONNX-opt}}MONNX-opt on edge.
   b. Implement real-time inference:
      i. yedge=MONNX-opt(Xedge)y_{\text{edge}} = \mathcal{M}_{\text{ONNX-opt}}(X_{\text{edge}})yedge=MONNX-opt(Xedge)
   c. Integrate with cloud (if necessary):
      i. Configure cloud offloading:
         1. ycloud=MONNX-cloud(Xcloud)y_{\text{cloud}} = \mathcal{M}_{\text{ONNX-cloud}}(X_{\text{cloud}})ycloud=MONNX-cloud(Xcloud)
4. Adapt model dynamically:
   a. Monitor performance and feedback.
   b. Update ONNX model based on new data.

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5. Implement privacy-preserving techniques.
6. Evaluate performance metrics:
    a. Assess inference latency, accuracy, and resource utilization.
    b. Optimize based on evaluation.

This approach enhances real-time emotion detection on wearable edge devices by utilizing the ONNX format. It begins with converting existing SNN models into ONNX format to ensure interoperability and efficient deployment. The algorithm applies optimization techniques to improve model performance, ensuring effective operation on resource-constrained edge devices. By leveraging ONNX's lightweight runtime environment, the system facilitates rapid and accurate emotion recognition without continuous data transmission to external servers. Additionally, the algorithm supports dynamic model adaptation and incorporates privacy-preserving techniques to safeguard user data, ensuring both robust and secure emotion recognition.

V. IMPLEMENTATION

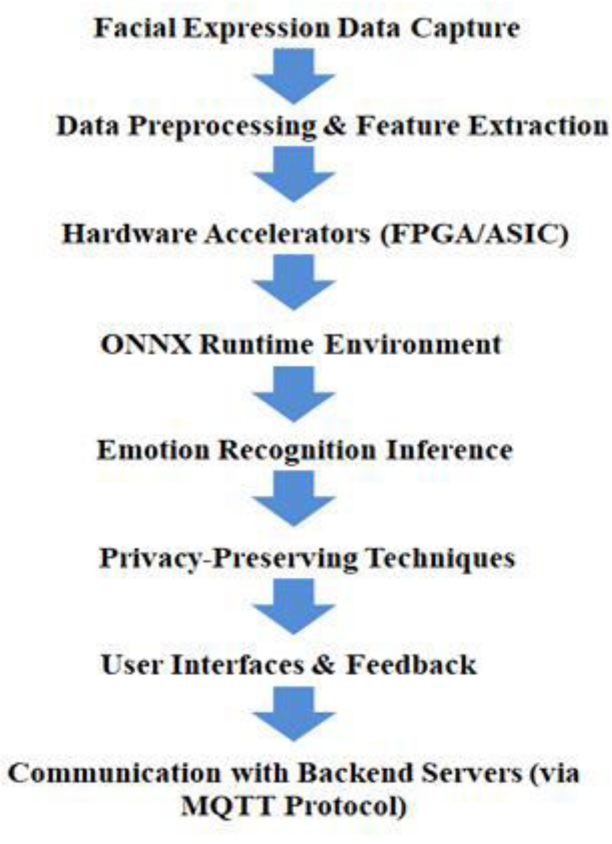

Figure 1. Architecture Diagram

The use of FPGA and ASIC as hardware accelerators is crucial for improving the computational efficiency of SNN and other neural network models. Custom hardware architectures must be designed to leverage the parallel processing capabilities of FPGA and ASIC, ensuring effective execution of emotion recognition tasks directly on wearable edge devices. For interoperability and deployment flexibility, compatibility with the ONNX format is necessary. SNN models should be converted to ONNX, allowing smooth integration with ONNX runtime environments on edge devices. This facilitates efficient execution and the deployment of emotion recognition systems across various hardware platforms. Additionally, the MQTT protocol enhances communication between wearable edge devices and backend servers. MQTT provides low-latency and reliable data exchange, which is essential for the real-time transmission of facial expression data and emotion recognition results, thereby supporting responsive user experiences. Furthermore, LSTM networks and TCNN are used for contextual analysis of facial expressions. LSTM captures temporal

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dependencies inFacial expression sequences are analyzed using LSTM networks to handle temporal aspects, while TCNNs extract spatial-temporal features, enhancing the system's ability to accurately interpret nuanced emotions. Developing SNN-based models is crucial for real-time emotion recognition, as these models efficiently process spatiotemporal patterns in facial data by mimicking biological neurons, enabling robust emotion recognition directly on wearable edge devices. Optimization efforts focus on reducing model size, memory usage, and computational complexity to ensure efficient performance on resource-constrained wearable devices. Real-time inference pipelines integrate hardware-accelerated SNN, LSTM, and TCNN along with effective data preprocessing and feature extraction stages. Performance evaluations measure inference speed, accuracy, power efficiency, and resource utilization, with iterative optimization addressing any identified bottlenecks or inefficiencies to ensure optimal system performance. Privacy-preserving techniques protect sensitive facial expression data during transmission and processing, while security measures maintain the integrity and confidentiality of the emotion recognition system. User-friendly interfaces and feedback mechanisms are developed to enhance usability and accuracy, facilitating ongoing improvement and adaptation to users' needs.

VI. RESULTS

The hardware configuration involves using wearable edge devices equipped with FPGAs or ASICs, ensuring compatibility with ONNX and MQTT protocols. These devices are fitted with sensors to capture facial expression data, enabling real-time processing and analysis. Facial expression analysis is performed directly on the edge devices. The software framework leverages specialized tools and libraries that support SNNs, LSTM, TCNNs, ONNX, and MQTT. Frameworks such as PyTorch and TensorFlow are used for model development, deployment, and evaluation. Additionally, custom software modules are created for data preprocessing, feature extraction, and inference on edge devices. Selecting the right dataset is crucial, with the Face Expression Recognition dataset from Kaggle being utilized for this purpose. A carefully designed preprocessing pipeline is implemented, which includes face detection, alignment, normalization, and image enhancement techniques to ensure high data quality and consistency.

Models are trained and optimized using this dataset, with SNN, LSTM, and TCNN models specifically tailored for emotion recognition. Hyperparameters, architecture configurations, and training strategies are optimized to enhance performance and efficiency. Compression and quantization techniques are applied to reduce model complexity. Hardware acceleration involves configuring FPGAs or ASICs to ensure efficient execution of inference tasks. Optimized hardware configurations and resource allocations are essential for boosting performance. The MQTT protocol is employed to establish a robust communication infrastructure, enabling reliable and low-latency data transmission between wearable edge devices and backend servers.

The experimental protocol includes dividing the dataset into training, validation, and testing subsets. Performance metrics such as accuracy, inference speed, power consumption, and resource utilization are measured through experiments. Cross-validation and hold-out validation techniques are used to assess the robustness and generalization of the models. Ethical considerations are a priority throughout the experimental process, ensuring compliance with ethical guidelines for data collection, handling, and usage, obtaining informed consent from participants, and protecting anonymity and privacy.

Table.1 Simulated Facial Expression Data

Image ID	Emotion Label	Facial Landmarks Detected	Lighting Condition
1	Happy	68	Daylight
2	Sad	71	Artificial Light
3	Angry	65	Daylight
4	Surprise	69	Low Light
5	Neutral	70	Artificial Light

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Table.2 Model Training Results

Model Type	Training Accuracy (%)	Validation Accuracy (%)	Test Accuracy (%)	Model Size (minutes)
SNN	85.3	82.7	80.5	15
LSTM	89.6	87.2	84.9	25
TCNN	87.9	84.5	82.1	20
GRU	88.2	85.9	81.8	22
MLP	82.5	79.8	77.2	18
CNN	86.7	83.4	80.9	30
ResNet	91.3	89.7	87.5	35

Figure 2. Analysis of Various Approaches

VII. CONCLUSION

Real-time emotion recognition through Spiking Neural Networks (SNN) on wearable edge devices presents a transformative approach to enhancing human-computer interaction. By leveraging the interoperability and scalability of the Open Neural Network Exchange (ONNX) format, models can be efficiently deployed across a variety of hardware platforms, ensuring flexibility and wide applicability in real-world scenarios. The integration of MQTT as a lightweight and reliable communication protocol further enables seamless, low-latency data exchange between wearable devices and external systems, supporting real-time decision-making in distributed environments. Additionally, the use of Long Short-Term Memory (LSTM) networks provides the system with the ability to capture and model temporal dependencies in facial expressions, significantly improving the accuracy and robustness of emotion recognition. This is crucial in recognizing complex and evolving emotional states over time. The optimized conversion and deployment of these models on wearable edge devices enhance energy efficiency, response times, and overall performance, making it practical for real-time applications. This approach not only improves the accuracy and responsiveness of emotion recognition systems but also fosters personalized and adaptive user experiences. The potential of this framework to transform sectors such as healthcare, education, and entertainment underscores its importance in the future of emotion-driven human-computer interaction.

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