Offline Edge-AI Model with CNN and Fuzzy Logic for Real-Time Human-Machine Interaction in Training Environments

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Abstract. This research introduces an Edge-AI Enabled Intelligent Training Model for real-time Human-Machine Interaction (HMI), designed for deployment in connectivity-constrained environments. The proposed hybrid architecture integrates Natural Language Processing (NLP), 1D Convolutional Neural Networks (CNNs), a Mamdani-type Fuzzy Inference System (FIS), and Reinforcement Learning (RL). Developed in MATLAB, the system ingests tokenized trainer and trainee answers to instructional prompts. These inputs are semantically embedded via separate CNN pipelines and fed into a fuzzy logic engine that interprets contextual meaning, tone, and correctness.

A cosine similarity score determines alignment between responses, and a reinforcement loop refines performance marking based on user validation. The model is ported to JavaScript for deployment in `Electron.js` and Android Studio, ensuring real-time, offline feedback on edge devices. A live demo is accessible at: `https://mytutor-ai.web.app/`.

This system offers a scalable, intelligent, and offline-capable performance assessment tool, especially relevant for cognitive and soft skill learning in low-resource settings.

Keywords: Edge AI · Human-Machine Interaction · CNN · Mamdani Fuzzy Logic · Reinforcement Learning · Offline AI · NLP · Intelligent Tutoring

1 Introduction

In resource-constrained educational environments, real-time, intelligent feedback is often lacking. This paper presents a hybrid Edge-AI model to bridge this gap by providing adaptive, offline Human-Machine Interaction (HMI) using NLP and fuzzy logic.

2 Methodology

The architecture begins with parallel NLP pipelines that tokenize both trainee and trainer inputs. These are passed through 1D CNN layers to extract semantic vectors. The outputs are evaluated using a Mamdani-type Fuzzy Inference

System that interprets subtle linguistic and contextual features. Cosine similarity quantifies semantic overlap, which is converted into a percentage score. Reinforcement learning adjusts scoring strategies over time based on trainer feedback.

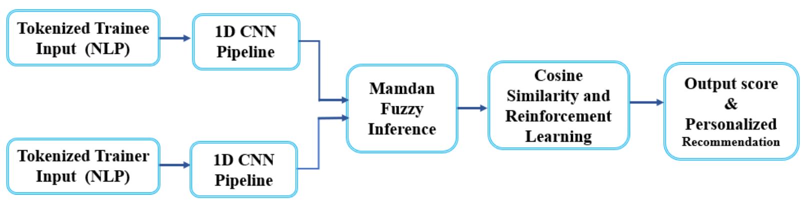

Fig. 1: Overview of the Edge-AI HMI model pipeline integrating NLP, CNN, Mamdani FIS, and RL

3 Results and Deployment

The prototype was built and tested in MATLAB. The trained CNN and FIS models were exported and embedded in a JavaScript framework for platform independence. A functional demo accessible via Electron.js and Android showcases its ability to operate entirely offline while delivering accurate, adaptive feedback. Demo: `https://mytutor-ai.web.app/`

4 Conclusion

This work contributes a portable, intelligent HMI system capable of assessing training responses with precision in constrained settings. It holds promise for scaling learning solutions across domains lacking infrastructure.

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