Optimizing Quantum Support Vector Classifiers in Flood Prediction: Data Specific Quantum Kernel Training for Enhanced Feature Mapping Capabilities

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Quantum Machine Learning (QML) addresses complex machine learning problems that deal with intricate relationships in complex datasets. When applied to real world datasets however, translating classical data into quantum data through feature mapping limits the models ability to analyze such relationships. Existing methods, such as the ZZ Feature Map, are not specific to the utilized dataset. I propose custom quantum circuits with qubits that represent features within a dataset, which are manipulated through entanglement principles in quantum gates, allowing for an accurate translation of the complex relationships in real world datasets. I programmed a Quantum Support Vector Classifier (QSVC) model utilizing the Qiskit framework, which is given the custom quantum circuit, run on a Quantum Kernel Trainer, creating a data specific featuremap. The optimized QSVC was trained and tested on the Flood Risk in India dataset, featuring 10,000 instances of floods and 13 features, such as humidity and elevation. Flood prediction is a complex task that involves taking into consideration various relationships between environmental factors. Not only was flood prediction the ideal candidate for experimentation, but it represents one of the various real world applications that the optimized QSVC can be applied to. The optimized QSVC was then compared to a QSVC ran using a ZZ Feature Map and a classical SVC to assess its accuracy. My results indicated that when trained with large amounts of data, the optimized QSVC significantly outperforms classical SVC models, bringing us one step closer to QML scalability, and applications to classical, real world, instances.

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