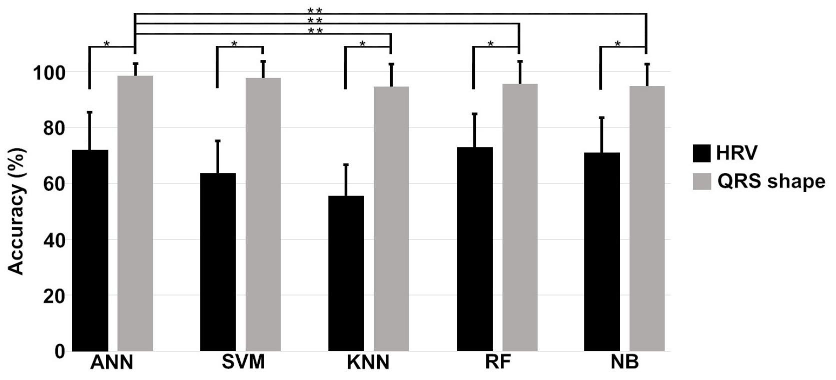

FIGURE 6 | Means and standard deviations of the prediction accuracies of each algorithm. Single asterisk (*) indicates a statistically significant difference between prediction accuracies using HRV and QRS shape features (QRS > HRV, $p < 0.001$), and double asterisk (**) between the prediction accuracies of different algorithms (ANN = SVM > KNN, RF, and NB, $p < 0.001$). HRV: heart rate variability with 11 parameters, QRS shape: QRS signed area and R-peak amplitude with 4 parameters, ANN: artificial neural network, SVM: support vector machine, KNN: k-nearest neighbors, RF: random forest, NB: Gaussian Naïve Bayes.

events occurred. They showed 76.6% accuracy for predicting VT and 92.2% accuracy for predicting VF. Recently, Lee et al. used RRV and HRV features to predict VT 1 h before it occurred. They showed a prediction accuracy of 85.3%, which is 10% better than their result when they used only HRV features (73.5%). The performance of our ANN model based on the QRS shape and HRV features was slightly higher than those of Elias et al. and Joo et al.'s result. Furthermore, we considered 30-s-long forecast time. However, Lee et al. considered a longer forecast time (1 h). Even though they considered longer forecast times, our ANN model showed higher accuracy.

Results show that features extracted from HRV contain important information for predicting the occurrence of VF several minutes in advance. However, Lee et al. (2016) revealed that the performance using only HRV features can be improved by adding RRV features. We found that only the QRS complex shape or that combined with HRV can improve the performance of predicting VF. In our study, we used 2-min-long signal to predict VF 30 s before its occurrence. The signals we used for the analysis (required time) and the prediction time gap (forecast time) were short. However, our study showed that the features extracted from QRS complex morphology (shape) could have effects for predicting VF.

We compared the performance obtained using a combination of HRV and QRS shape features with that obtained using only QRS shape features, but little improvement in prediction accuracy (only ∼1%) was found for the combination features. This indicates that using QRS shape features solely would be an efficient way to predict VF. Therefore, we decided to not include the result for the combination features in our study.

Our algorithm could be installed in patients' implantable cardiac defibrillator (ICD) for real-time VF prediction as an additional functionality to VF detection. Predicting the occurrence of VF hours in advance would be more useful, however, the datasets used for this paper limited to 120 s data window and predict VF 30 s before its occurrence. Au-Yeung et al. (2018) showed that a correct prediction could be made when the ventricular arrhythmia occurs nearer. Thus, our prediction accuracy of 98.6% was higher than that of Bayasi et al. (2016) who predicted the occurrence of VF 3 h prior to the onset with an accuracy of 86%, and Lee et al. (2016) who predicted the onset 1 h prior with an accuracy of 85.3%.

According to the Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, a recording of approximately 1 min is needed to calculate the HF component, and at least 2 min, to calculate the LF component (Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996). However, the VLF calculated from short-term recordings (<5 min) is an uncertain measure (Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996). The VF datasets in this study were very short in length, therefore, we had to use 120 s data window for extracting features 30 s before VF occurs.

The limitation of our study was the small dataset (55 recordings) and the short length of the signals before the VF occurred. To implement a study for clinical purposes, our ANN model must be trained using more datasets.

CONCLUSION

In this study, we used an ANN to predict the VF using features extracted from 120 s HRV signals, the QRS complex signed area, and the R-peak amplitude 30 s before VF occurrence. The datasets were collected from the popular physiological archive PhysioNet. Although the datasets utilized in this study were relatively small, the performance of the ANN was better using QRS shape features than that of traditional HRV features. This was consistently observed in all machine learning algorithms implemented in this study, which demonstrates