Top Architectures Overview

2. 1D CNN with GRU and Resnetblock (1DCNNGRU)

Architecture: A hybrid model architecture with a 1 dimentional convolutional network with resnet blocks and a GRU

Layer Type	Description
ConvBlocks1D	1D Convolution: kernel_size=3, stride=1, padding=1; followed by ReLU activation and BatchNorm1d
ResNetBlocks1D	Residual Block: Two 1D Convolutions (kernel_size=3, stride=1, padding=1), followed by ReLU activation and BatchNorm1d. Includes a skip connection.
MaxPool1d	Max Pooling: kernel_size=2, stride=2. Reduces the sequence length by half.
Linear	Linear Layer: Flattens the output of convolutions, transforming the features into a flatten vector.
GRU	GRU Layer: input hidden units, input number of layers, batch_first=True, dropout for regularization
Dense Layers	GRU output (batch_size, hidden size) is flattened into a 1D vector (batch_size, hidden size). 2 Fully connected Layers: hidden size input features, hidden size output features with ReLu Activation, 5 output features (final classification).

2. 2D Convolutional Neural Network (CNN) with ResNet block

The model is a 2 dimentional convolutional network with a Resnet block **Architecture**:

Layer Type	Description
Convolutions blocks	Conv2d hidden size input channel, hidden size output channels, kernel size 3x3, stride 1x1, padding 1x1, with ReLU activation and BatchNormalization
ResNetBlock2D	2 Conv2d layers, hidden size input/output channels, kernel size 3x3, stride 1x1, padding 1x1
	followed by ReLU activation and Batch Normalization 2D
MaxPool2d	Identity layer (preserve the input) followed by MaxPool 2D layer Kernel size 2x2, stride 2x2
Dense Layers	Flatten input tensor starting from the first dimension
	2 Linear layers with input flattened features, hidden size output/input followed by ReLU activation with final 5 output classes

HYPERTUNING SEARCHSPACE

The hyperparameters of the model were optimized using the following search space (top 10 models):

Model	Batch Size	Hidden units GRU	Hidden units CNN	Number of Layers	Number of blocks	Dropout Rate	Factor (ReduceLROnPlateau)
1DCNNGRU	[16, 32, 48, 60]	[32, 64, 128, 256, 512]	[32, 64, 128, 256, 512]	[2, 3, 4]	[1 - 5]	[0.2, 0.3, 0.4]	[0.1 - 0.4]
2DCNN	[16, 32, 48]		[62 - 256]	[2, 3, 4]	[1 - 7]	[0.1 - 0.4]	[0.1 - 0.4]

Best configurations for the two model (30 epochs) with a balanced oversambled traindata:

Model	iterations	accuracy	recallmacro	batch	hidden	dropout	num_layers	num_blocks	factor	gru_hidden
2DCNN	30	0.9888	0.9744	16	128	0.3	3	1	0.2	--
1DCNNGRU	28	0.9858	0.9593	32	64	0.4	2	5	0.2	256

Hyperparameter tuning began with a manual exploration of parameter ranges, such the ranges of number of blocks and layers and Bayesian Optimization function in Ray HyperOptSearch from Ray Tune for hyperparameter optimization. HyperOptSearch searches space probabilistically and uses the observed performance of previous trials to make predictions about which hyperparameters are most likely to yield good results. In the second stage of tuning, the process expanded to test other important factors such as batch size, optimizer choice and scheduler types as parameter of the configuration. Some parameters suche optimizer and sheduler are not included in the table above

because default parameters from manual testing performed better. The models have been trained with 30 and later to 40 epochs with early stopping. Longer training did not improve accuracy on both on the smote and oversampled dataset.

RESULTS AND REFLECTIONS

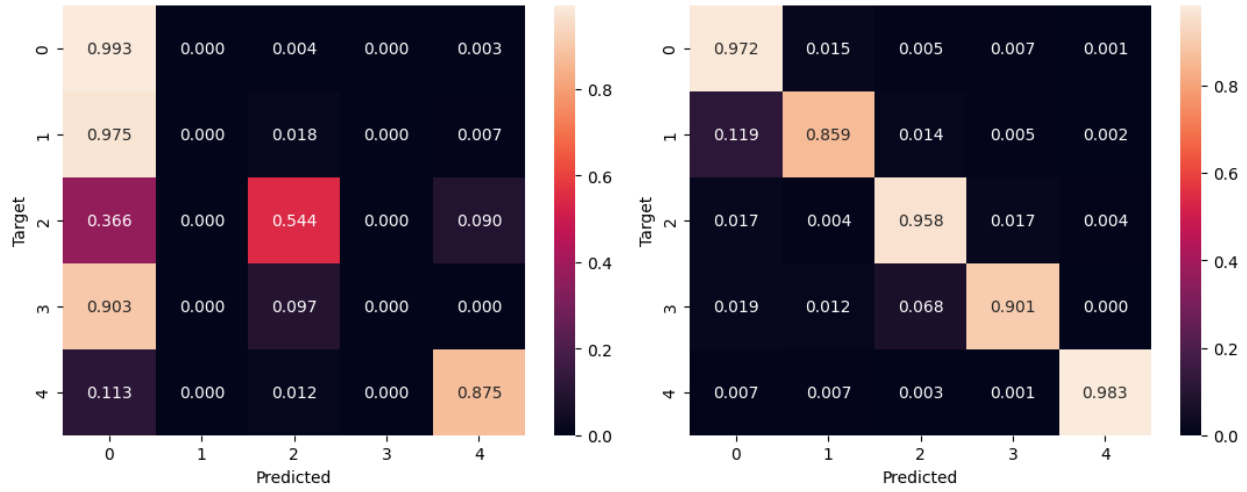
Hypothesis and results

The initial hypothesis was that 1D models, specifically GRU and 1D CNN, would be a better fit for the training set due to the sequential nature of the data. This hypothesis was confirmed: 1D models performed well, but a significant amount of experimentation was required, especially in relation to the dataset.

Counter-Hypothesis: The hypothesis that 2D models would overfit or be too complex for the time-series dataset turned out to be false. The 2D CNN emerged as the best-performing model with the highest accuracy and recall on the oversampled dataset.

Key Discoveries: Dataset Imbalance: From the start, the 1D models' performance was hindered by the dataset's imbalance. Despite efforts to address this issue through architectural changes, the almost all the 1D models overfit to the majority class and underperformed. This led to further exploration of Transformers and 2D CNN models, which seemed to handle the imbalanced dataset a little better. This led to exploring more models and solutions than initially planned, which was useful for deeper insights. Balancing the dataset should have been the first step in the exploration before exploring alternatieves!

Model Insights: GRU Models: GRU models can be slow and computationally expensive to train due to their recurrent nature. The idea that they are fit for analysing time series is partially true. DThe update and reset gates in GRUs might learn to favor the dominant class, this model might "memorize" the majority class patterns more easily. Because they have the capacity to remember long-term dependencies, they may effectively "ignore" the minority class, treating it as less significant (or even as "noise"). However, this can be mitigated by hybrid architectures that combine CNNs and GRUs. In these hybrid models, CNN layers efficiently extract features from the input data, and GRU layers capture temporal dependencies or sequential patterns within those features avoiding the overfitting. The model trains faster using parallel CPU's and requires less resources because it reduces complexit through convolution. Although GRUs initially struggled with imbalanced datasets, they performed well with upsampled and synthetically modified datasets, but the training time was really a huge problem. Also other models suffered from overfitting to the majority class but the GRU was extreme. To show the difference, here is a confusion matrix from the GRU model performace with the unbanced dataset vs the performance of hybrid GRU model with Resnet block (5 epochs):



1D CNN with GRU

2D CNN: The 2D CNN architecture performed exceptionally well on this dataset, even with synthetic or oversampled data. It handled semi-imbalanced data effectively and was fast to train. The 2D CNN was surprisingly effective given that time-series data usually works better with 1D CNNs. Despite being a more complex model, the 2D CNN worked well due to its ability to capture spatial features. The addition of residual blocks helped retain more information and avoid overfitting, making this model quicker to train and delivering top results.

2D Transformer: Implementing 2D convolutions within the transformer architecture was an innovative approach and provided better results than 1D convolutions. The 2D convolutions allowed the model to capture more detailed spatial features, complementing the transformer's self-attention mechanism. However, this approach was too complex for this task, as the training took significantly longer and required more computational resources.

Additional Blocks: ResNet Blocks: Both CNNs and Transformers worked well with ResNet blocks. These blocks improved performance by helping the model learn more complex features and allowing it to focus on local patterns, improving generalization and maintaining consistent performance throughout training.

Squeeze-and-Excitation (SE) Block: The SE block added significant value to Transformer architectures by enhancing their ability to focus on the most important features. However, it didn't provide much benefit to CNNs, where the convolutional layers already focus on local patterns

like edges and textures. CNNs don't necessarily require the same level of global feature recalibration that SE blocks provide.

Transformers and Synthetic Data: Transformers were less adaptable to synthetic data like the one generated with SMOTE. They seemed to detect the synthetic data as noise, which may have impacted their performance on the altered dataset.

Useful Fine-Tuning Options: Dilated Convolutions: The dilation parameter in convolutional layers helps capture a larger temporal context, increasing the receptive field by spacing out the kernel. This allows the model to capture long-range dependencies in the data while keeping the kernel size fixed.

MaxPooling vs. Global Average Pooling (GAP): MaxPooling helps capture peak values in time-series data, while GAP tends to aggregate the features over the entire sequence. Depending on the task, one may be more beneficial than the other.

Packed Sequences: The pack_padded_sequence function helps RNNs handle variable-length sequences by converting padded sequences into a packed format. This enables the network to ignore padded values during training, improving efficiency.

Other Learnings and Insights: I experimented with hyperparameter tuning of optimizers, patience, batch size, and schedulers. I discovered that default values often performed quite well, saving computational resources without sacrificing performance.

I also learned that without setting a random seed in the configuration, it becomes impossible to reproduce the exact model that was trained. Therefore, I included a random seed in the configuration for reproducibility.