Project Report - Master Informatics

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Course: Machine learning

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Project repo: https://github.com/FP-byte/MADS_EXAM-25_FP

Top Architectures Overview

1. 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

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

Layer Type	Description
Convolutions blocks	Conv2d block with given hidden size as 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 oversampled 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 started with manual exploration of parameters like the number of blocks and layers, followed by hypertuning using Ray Tune's HypeOptSearch. This method probabilistically searches the space, using previous trial performance to predict optimal hyperparameters. During hypertunring additional factors like batch size, optimizer, scheduler and dataset were tested. These parameters not reported on the table for lack of space. Models were trained for 30 to 40 epochs with early stopping, as longer training did not improve accuracy on either the SMOTE or oversampled datasets.

RESULTS, REFLECTIONS AND KEY LEARNINGS

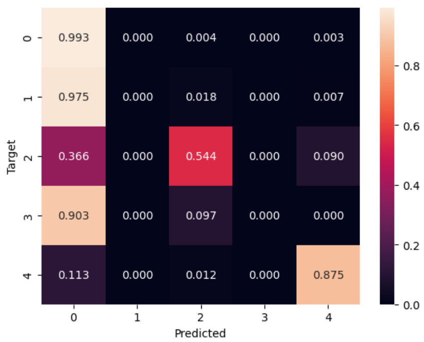
The **initial hypothesis** was that 1D models, specifically GRU and 1D CNN, would be a better fit for the training set due to the sequential nature of the data. This hypothesis was confirmed: 1D models performed well, but a significant amount of experimentation was required, especially in relation to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

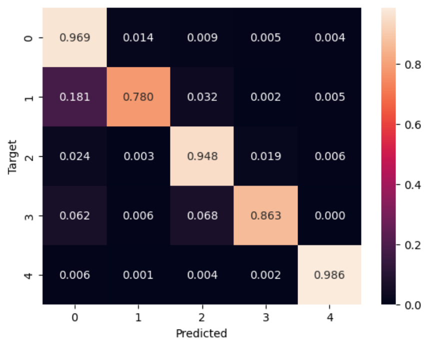
Dataset Imbalance: From the start, the 1D models' performance was hindered by the dataset's imbalance. Despite efforts to address this issue through architectural changes, the almost all the 1D models overfit to the majority class and underperformed. This led to further exploration of Transformers and 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!

GRU Model:GRU Model: While GRUs are well-suited for sequential data, they can be slow and computationally expensive to train due to their recurrent nature. Their ability to capture long-term dependencies can be a double-edged sword: the update and reset gates may favor the dominant class, causing the model to "memorize" patterns of the majority class and potentially ignore the minority class as noise. Although GRUs initially struggled with imbalanced datasets, they performed well with upsampled and synthetically modified datasets, but the training time was a significant challenge. However, this issue can be mitigated through hybrid architectures, where CNN layers are used to efficiently extract features and GRU layers capture temporal dependencies within those features. These hybrid models reduce overfitting, train faster using parallel processing, and are less resource-intensive due to the convolutional layers simplifying the model's complexity scale. Also, other models suffered from overfitting to the majority class, but the GRU was particularly extreme in this regard. To illustrate the difference, here is a confusion matrix comparing the GRU's performance with an imbalanced dataset versus a SMOTE-modified dataset, as well as a CNN-GRU hybrid model (trained for 5 epochs):

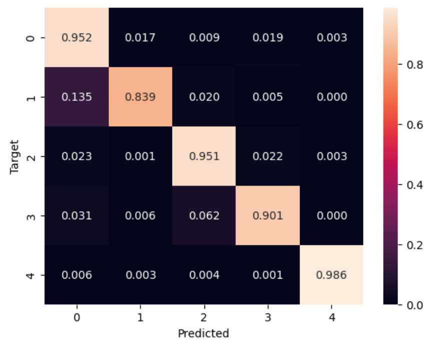
GRU with imbalanced dataset



GRU with balanced smote dataset



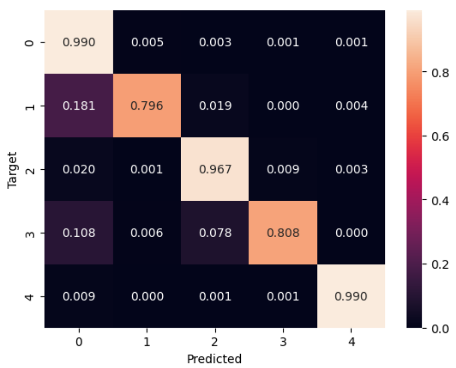
Hybrid CNN+GRU with smote dataset



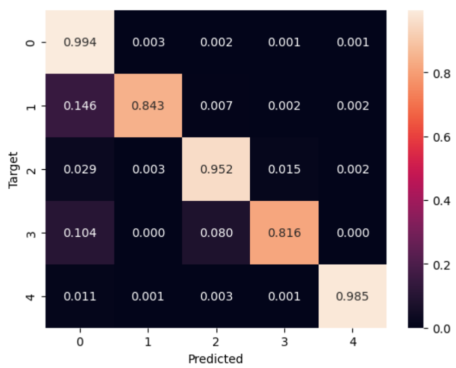
2D CNN: The 2D CNN architecture performed exceptionally well on this dataset, especially with synthetic or oversampled data. It handled also semi-imbalanced data effectively and was fast to train. Despite being a more complex model, the 2D CNN worked well due to its ability to capture spatial features. The addition of **residual blocks** helped retain more information and avoid overfitting, making this model quicker to train and delivering top results. Adding shortcut connections in CNNs and also Transformers allowed for deeper models and better training.

Here is the performance of the Hybrid GRU model vs the 2D CNN trained for 30 epochs with the best configuration:

Hybrid 1D CNN with GRU



2D CNN with Resnet



This project has been quite a long journey of exploring different models, filled with valuable learning and insights. If starting over, I'd focus on thorough dataset analysis and systematic model comparisons with consistent configurations and training epochs.