Thesis 2021

Australia's Global University | Faculty of Engineering | School of Electrical Engineering and Telecommunications

# End-to-End Deep Learning Automated Insomnia Diagnosis


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## 1. Background and Motivation

- The **EEG** (electroencephalography) signal can determine if a patient is insomniac.
- Clinical diagnosis is time consuming, requires expertise, and suffers from a lack of objective benchmark.
- **Machine learning** models have been used, but require complex and hand-crafted feature engineering.
- **End-to-end deep learning models** can learn abstract features and don't require domain specific knowledge.

## 2. Thesis Aims

**Investigate the performance of end-to-end deep learning models for insomnia classification.**

1. Investigate the use of a 1D CNN.
2. Investigate the use of a spectrogram with 2D CNN.
3. Compare different train and test splitting methodologies.
4. Explore whether data augmentation techniques lead to improved model performance.

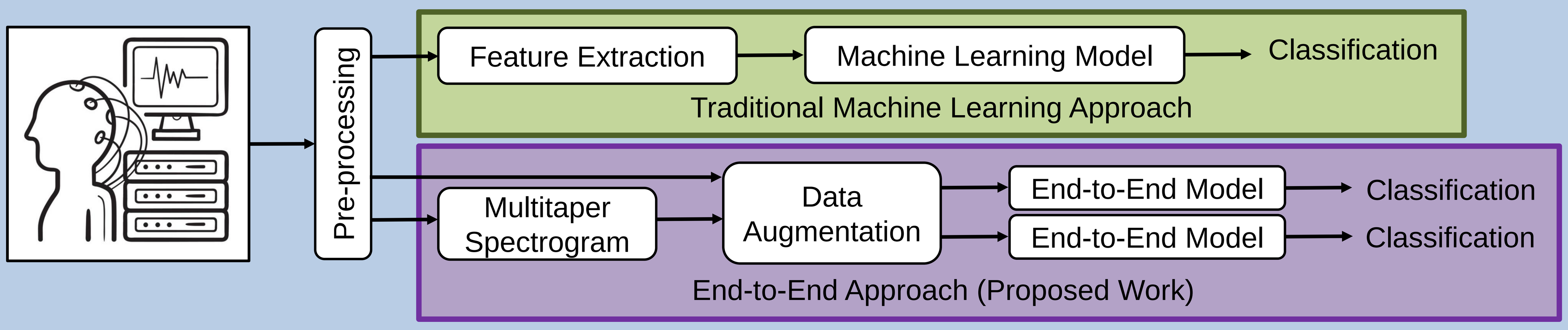


*Figure 1: System diagram comparison between machine learning and end-to-end approaches*

## 3. Pre-Processing

- 0.5-40Hz bandpass FIR filter with Hamming window
- 128Hz resampling
- Division into 30s frames
- 3840 samples per frame
- > 250μV artefact removal
- Adjusted for DC offset
- Frame insomnia/control labelling

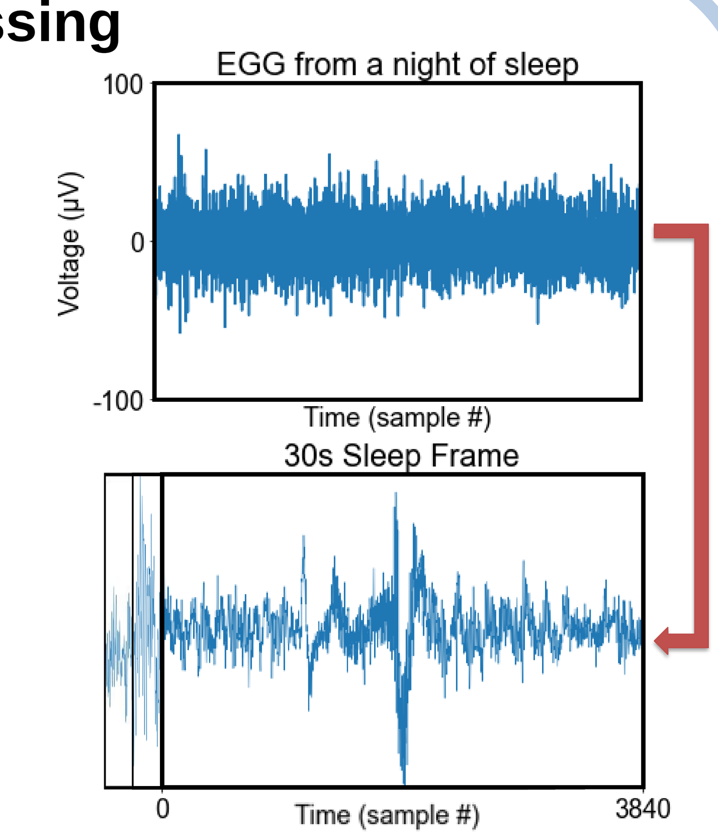


*Figure 2: Pre and post-processed EEG*

## 4. Multitaper Spectrogram

A **low bias and low variance estimator** of the spectral content, providing high-resolution EEG spectrograms compared to the single-taper spectrogram. The orthogonality property of DPSS tapers enables uncorrelated single-taper spectral estimates to be averaged to produce the multitaper spectrogram.

Parameters: $N = 5s$; $\Delta f = 1Hz$; $TBW = N\Delta f = 5$; $\#\,Tapers = \lfloor TBW \rfloor - 1 = 4$

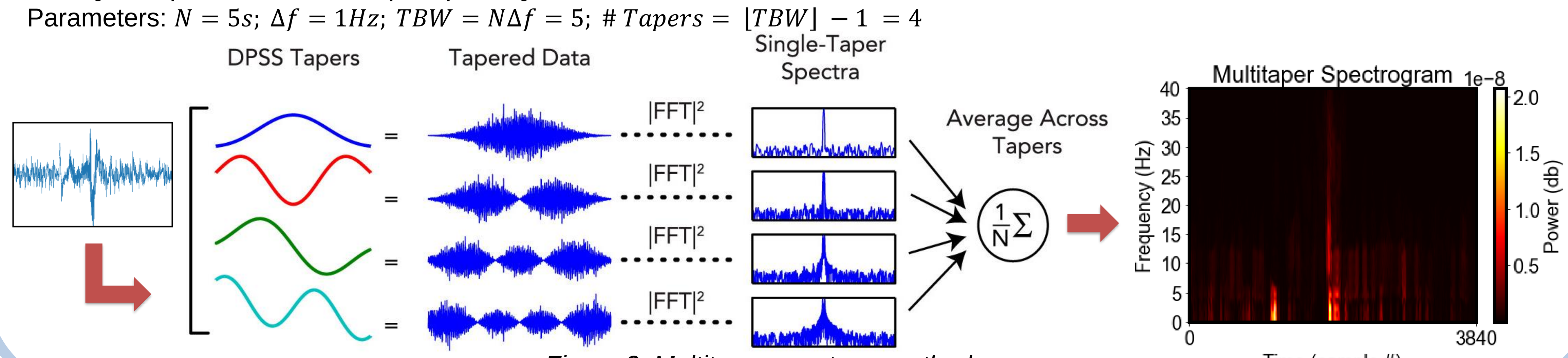


*Figure 3: Multitaper spectrum method*

## 5. Data Augmentation

**Offline** data augmentation **expands** the existing dataset with additional samples.

**Online** data augmentation **replaces** the existing dataset with random augmentations.

Together this leads to **improved generalisability**.

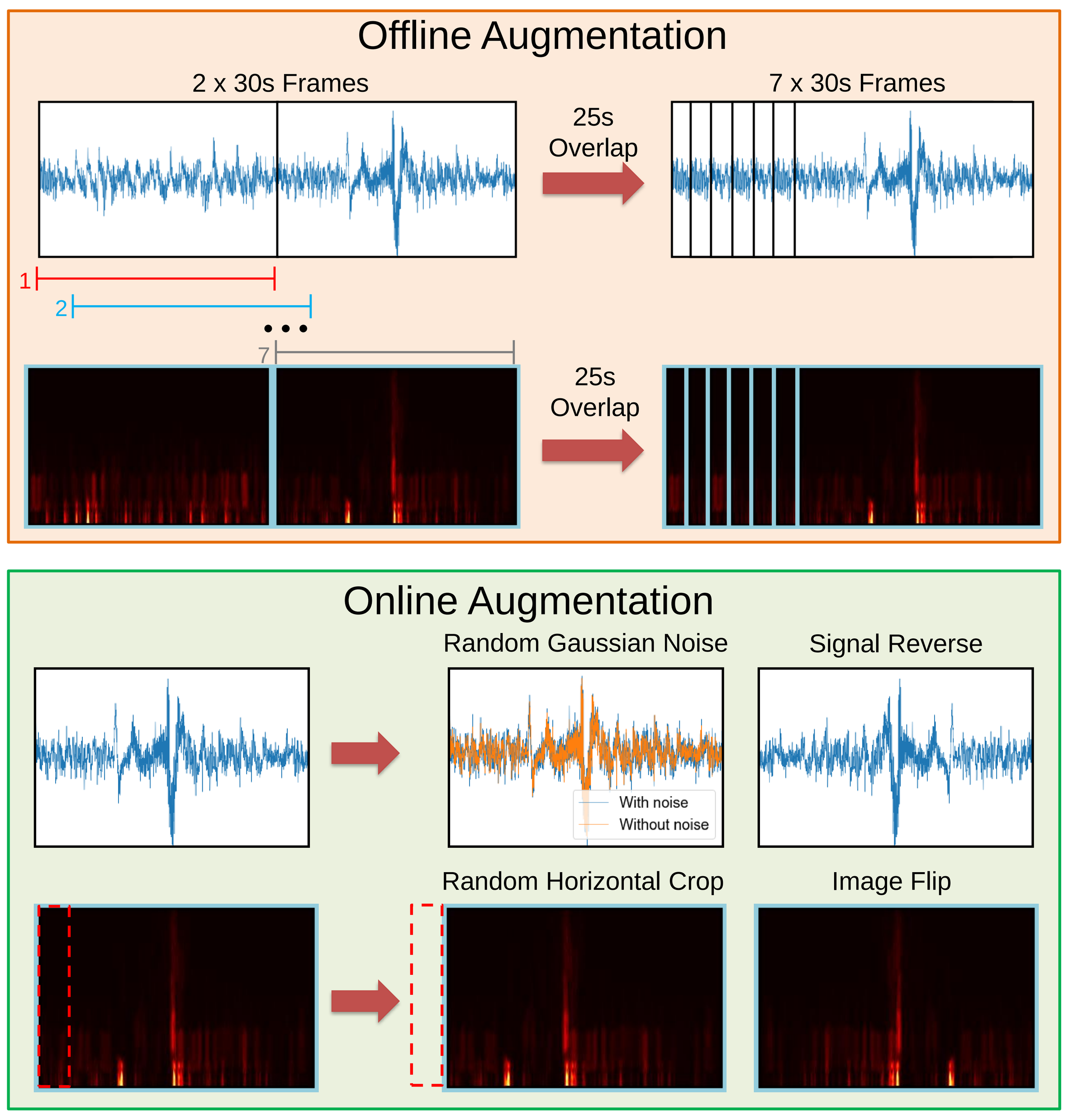


*Figure 4: Methods of data augmentation*

## 6. Train Test Split

**Inter-patient** dataset splitting ensures generalisability for unseen patients.

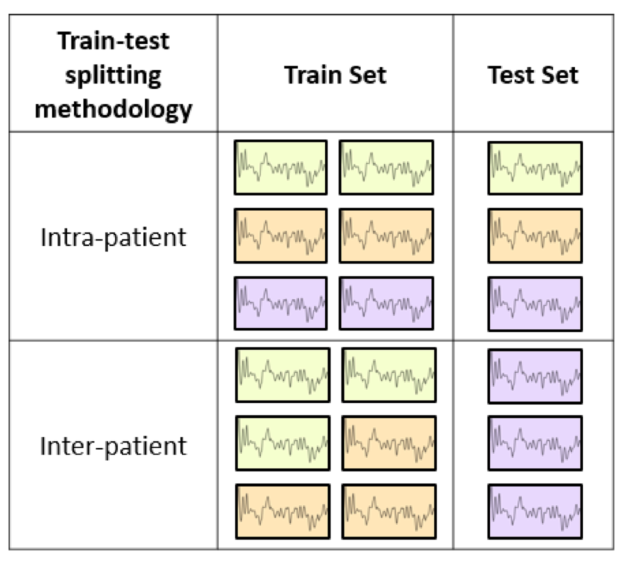


*Figure 5: Intra vs inter-patient split*

## 7. Model Architecture

**AlexNet 2D** is a 2D CNN that embeds a 227 x 227 spectrogram image as input.

**AlexNet 1D** is a variant of AlexNet 2D that embeds the 3840 time-series EEG data as input.

Dropout and regularisation techniques are employed to reduce overfitting.

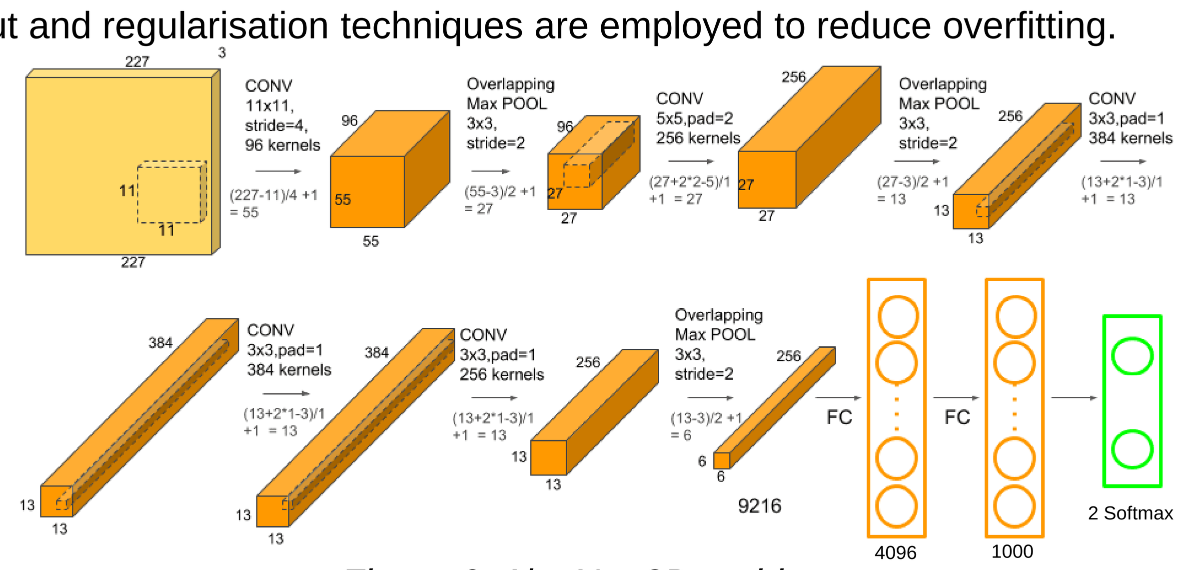


*Figure 6: AlexNet 2D architecture*

## 8. Results

Both models were trained on SWS sleep stage frames, utilising 9-fold cross-validation, maximum 150 training epochs, early stopping, and output class balancing.

| AlexNet 1D | | | |
|---|---|---|---|
| Split | Data augmentation | | Accuracy |
| | Offline | Online | |
| intra | Overlap | All | 0.957767 |
| intra | Overlap | Reverse | 0.944375 |
| intra | Overlap | Noise | 0.992735 |
| intra | Overlap | None | 0.993139 |
| intra | None | All | 0.8079 |
| intra | None | Reverse | 0.814815 |
| intra | None | Noise | 0.8836 |
| intra | None | None | 0.874581 |
| inter | Overlap | All | 0.663465 |
| inter | Overlap | Reverse | 0.679058 |
| inter | Overlap | Noise | 0.668703 |
| inter | Overlap | None | 0.650091 |
| inter | None | All | 0.650731 |
| inter | None | Reverse | 0.607176 |
| inter | None | Noise | 0.628702 |
| inter | None | None | 0.604967 |

| AlexNet 2D | | | |
|---|---|---|---|
| Split | Data augmentation | | Accuracy |
| | Offline | Online | |
| intra | Overlap | All | 0.889189 |
| intra | Overlap | Reverse | 0.902398 |
| intra | Overlap | Crop | 0.88409 |
| intra | Overlap | None | 0.899208 |
| intra | None | All | 0.760884 |
| intra | None | Reverse | 0.830407 |
| intra | None | Crop | 0.765737 |
| intra | None | None | 0.781965 |
| inter | Overlap | All | 0.550853 |
| inter | Overlap | Reverse | 0.55022 |
| inter | Overlap | Crop | 0.573697 |
| inter | Overlap | None | 0.53786 |
| inter | None | All | 0.510317 |
| inter | None | Reverse | 0.490079 |
| inter | None | Crop | 0.522771 |
| inter | None | None | 0.514509 |

*Figure 7: Parameters and average test accuracy of model instances*

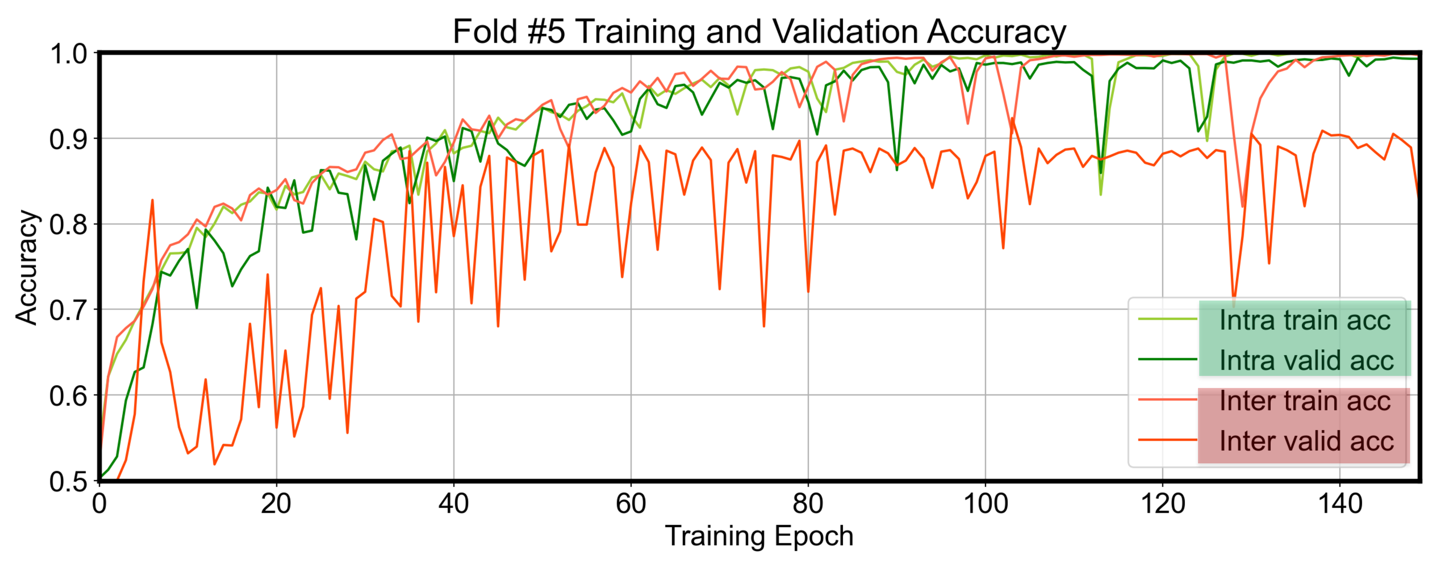


*Figure 8: Training and validation accuracies between intra and inter-patient split for highlighted model instances in Figure 7*

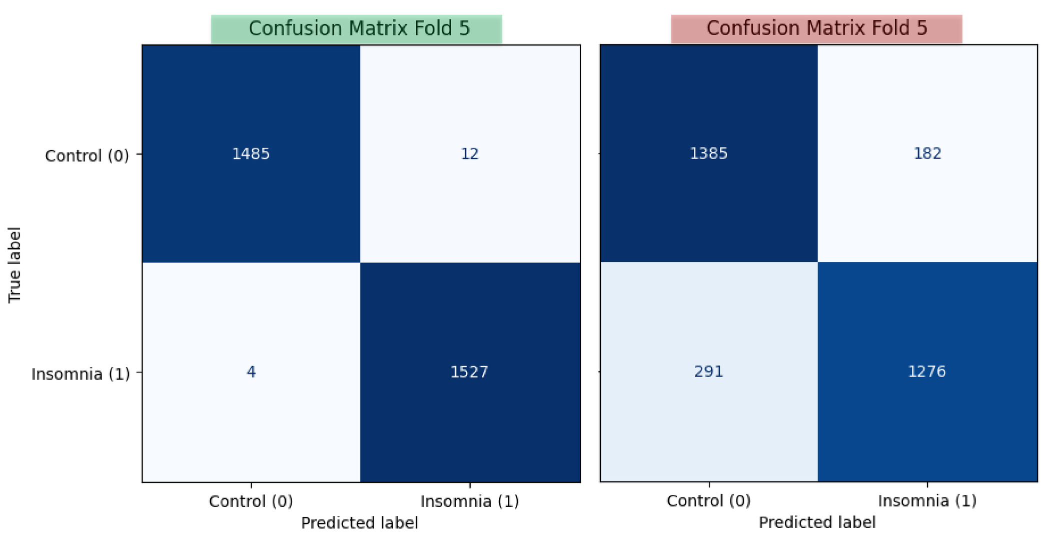


*Figure 9: Confusion matrix between intra (left) and inter-patient (right) split for highlighted model instances in Figure 7*

## 9. Conclusion

- AlexNet 1D is capable of achieving state-of-the-art performance (>95% acc) with intra-patient splitting, with or without data augmentation.
- **Splitting**: models tend to learn **patient-specific features** rather than insomnia-related features, therefore has trouble in generalising to unseen patients.
- **Model**: A 1D CNN with time-series input performs better than a 2D CNN with spectrogram input
- **Offline augmentation**: improves performance across all model instances.
- **Online augmentation**: yields none or slightly improved performance for poorly performing models (50-70% acc); degrades performance on well-performing models (> 80% acc).

## 10. Future Work

- Train on alternative sleep stages (N1, N2, REM); incorporate multiple datasets.
- Expand model to include patient-level classification.
- Explore advanced data augmentation techniques (GANs, frequency shifting).
- Implement alternative CNNs (ResNet, VGGNet, EEGNet).
- Test on other types of end-to-end networks (LSTMs) and ensemble methods.
- Experiment with multitaper spectrogram parameters.
- Evaluate model suitability for other EEG classification problems (motor imagery BCI, other mental disorders, sleep stage classification).