



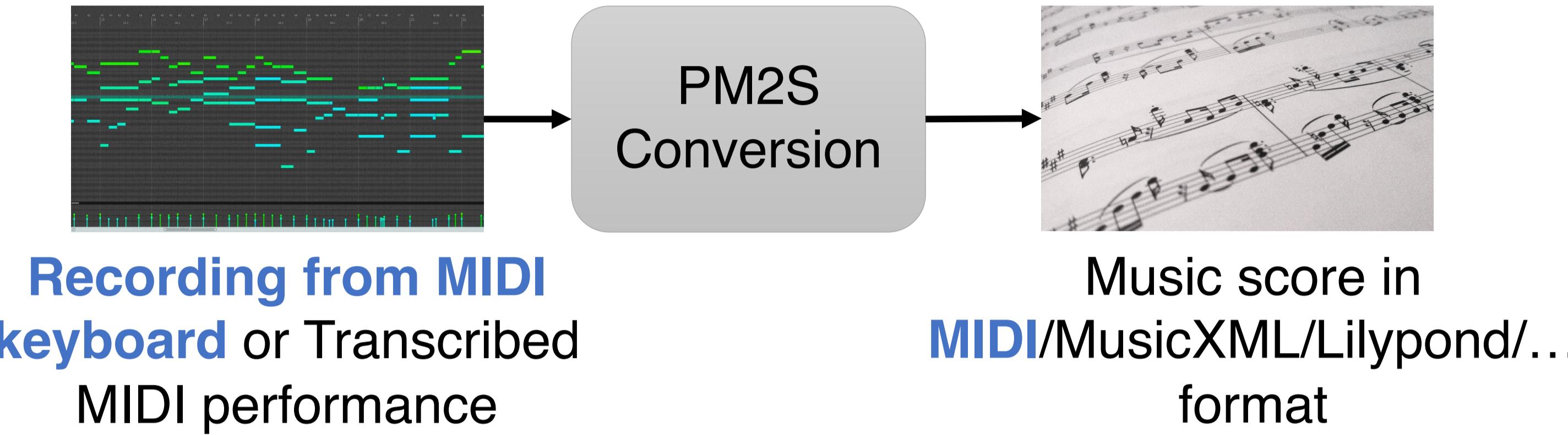
Performance MIDI-to-Score Conversion by Neural Beat Tracking

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I. Performance MIDI-to-Score (PM2S) Conversion

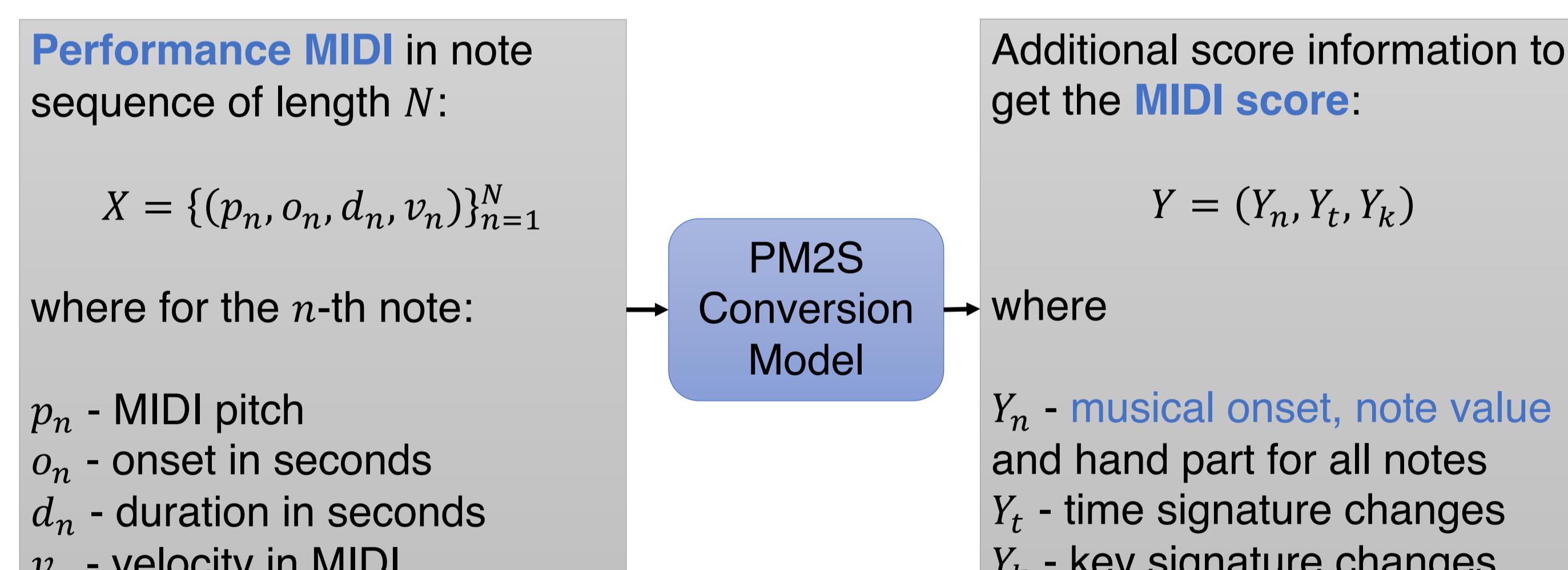


- **Applications:** Music improvisation, complete music transcription, music performance analysis
- **Subtasks:** Rhythm quantisation, note value prediction, key estimation, voice separation, and possibly score type-setting such as beaming and playing techniques annotation

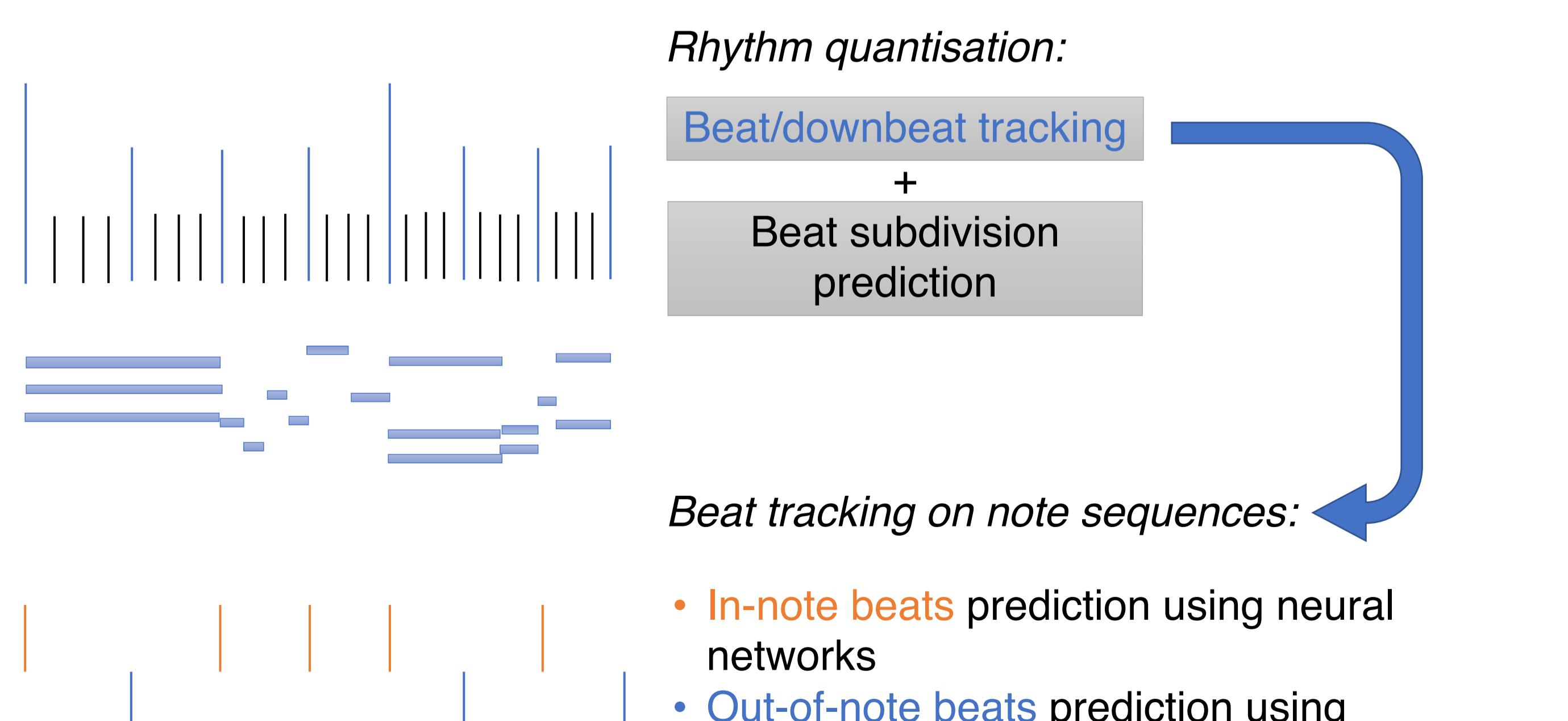
II. Contributions

- A deep learning (CRNN) model with a compact output for PM2S
- A new rhythm quantisation method by tracking beats on a MIDI note sequence
- Comparisons between different input encodings of MIDI note sequences for tracking beats from performance MIDI
- Ablation studies on input features and data augmentation methods for tracking beats from performance MIDI
- A PM2S conversion toolbox

III. Methodology



Rhythm quantisation: the prediction of musical onset and note value for each note in the note sequence



- For **in-note beat prediction**, we use a CRNN model
- For **out-of-note beat prediction**, we design an objective function to be minimized that encourages **a low level of tempo change** and add **fewer out-of-note beats**

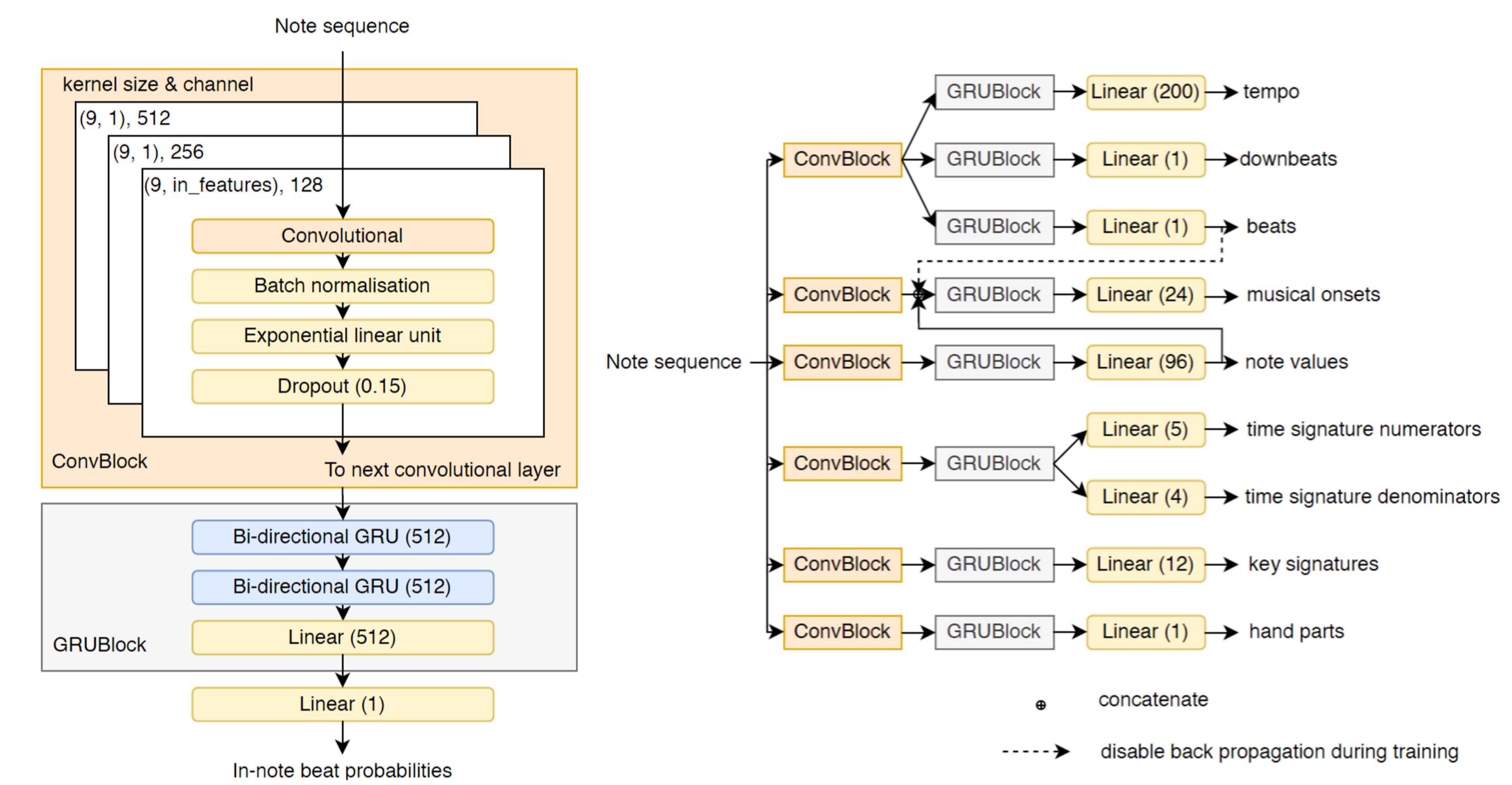
$$\mathcal{O} = \sum_{n=1}^{N-2} \left| \log\left(\frac{b_{n+2} - b_{n+1}}{b_{n+1} - b_n}\right) \right| + \lambda \times N^o$$

b_n – n -th beat time in the in-note beats list

λ – penalty coefficient for adding out-of-note beats

N^o - number of out-of-note beats

- We further **expand the CRNN model to predict a compact output data representation** for musical scores



IV. Experiments

- We use a collection of classical piano performances and scores, in total 123.2 hours of piano performances in 504 distinct pieces.
- The train/valid/test splits do not have overlapping pieces
- Comparative experiments show that:
 - Using MIDI pitch, onset shift in one-hot format, duration in raw values, and velocity achieves best performance among difference input data encoding combinations
 - All four input features are helpful
 - Using data augmentation during model training is beneficial
 - Our proposed beat tracking model outperforms a baseline beat tracking model

MV2H evaluation on performance MIDI-to-Score Conversion:

Methods	F_p	F_{vo}	F_{me}	F_{va}	F_{ha}	F
Finale	82.2	54.6	9.9	92.2	86.2	65.0
MuseScore	10.0	65.0	15.3	95.0	84.5	54.0
Proposed	99.8	87.0	61.7	99.9	91.1	87.9

- Results show better performance can be achieved by our model in comparison with two commercial software (Finale and MuseScore), based on the MV2H metric.
- Significantly better performance can be observed in the metrical alignment metric, due to our method's ability to track tempo changes.

