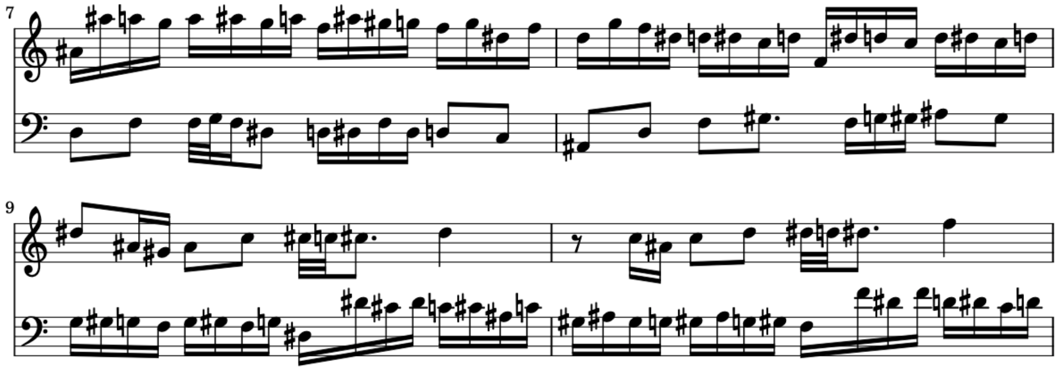

Optical Music Recognition for Homophonic LilyPond File Generation

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Executive Summary

abstract goes here...

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1 INTRODUCTION

1.1 Initial Proposal

TODO: Introduction citations [2**?** , 3]

In the world of music or audio transcription/arrangement, the complexity of sound and score data has allowed human performance to remain the current state-of-the-art. Several factors contribute to this circumstance: the number of potential audio and score file types, ambiguity on how performance qualities are notated, and overall inconsistencies between recordings and their respective scores. Machine learning models, in turn, have been a crucial step towards reducing these inconsistencies. Their ability to learn the nonlinearities and artistic qualities that otherwise plague audio computation have allowed for noteworthy advancements such as the WaveNet [9]. The remaining issue in the process of sound generation is the amount of data available to train with. Worthwhile audio data remains difficult to collect due to its large size and potential copyright issues. In particular, trying to condition off another medium is incredibly difficult as current datasets lack the correlations necessary to streamline the audio transcription process. Datasets such as MAESTRO [4] are close to ideal results, but some intermediate steps are needed to learn correlations between audio files and musical scores.

With the following conditions in mind, I propose an Image-to-MIDI model to serve a few purposes. First, this model serves to convert image data to relative musical data to a high degree of accuracy. The process of converting MIDI to an image is trivial, but the opposite is a known Optical Music Recognition (OMR) problem in that the correlation is nonexistent. Second, a highly reliable model of this type is capable of serving as an intermediate step in future audio computation endeavors, as the nontrivial nature of OMR is a barrier for reliable model training between scores and other types of audio data. Finally, a conversion of this type allows for more flexible datasets because MIDI can be converted into a number of other audio file types.

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1.2 Known Limitations

Given the vast complexity of western music notation and intricacies in notation/time alignment, the proposed model has a pessimistic approach. That is, given a small subset of musical data (*among all notated music*) and some model, results can be expected to only match expected outputs through one or more of: pitch, rhythm, duration, and overall formatting. Existing research in OMR supports these expectations. First, several digital notation systems exist for music, including:

- Standards like *MusicXML*, *Lilypond* and *MIDI*,
- Software-specific formats from *Musescore*, *Sibelius* and *Finale*,
- *KERN* from the Humdrum tool-set [**?**],
- Mayer, et al.'s *Linearized MusicXML* [6], and
- Contreras, et al.'s untitled "end-to-end OMR" encoding language [2].

Each format provides benefits and drawbacks towards generalized OMR, but combined research efforts have yet to hone in on a particular format. Second, current research continues to limit its effective musical scope: constant genre, time period composed, single vs. multi-line pieces, and single vs. multiple measures, to name a few. These limitations are to be expected as a means of balancing experiment accuracy with the subset of musical notation to be recognized. However, no paper to date has intended to capture a high accuracy while completely generalizing the space of recognizable music.

Finally, the state-of-the-art for machine-learning-based OMR lies in the implementation of Convolutional Recurrent Neural Networks (CRNN). This model type is preferred over CNN for its ability to learn data as order-dependent sequences- a crucial philosophy in parsing and understanding musical scores in general. However, it should be noted that CNNs are still viable for their non-order-dependent musical problems, such as Nugroho and Zahra's work on individual note and duration recognition [7].

1.3 Research Questions

Despite low research expectations, I believe that a few questions can be posed and answered for the purpose of bounding requirements on a larger, all-encompassing Image-to-MIDI model:

RQ1 What forms of recognition can be expected from a generalized CRNN implementation?
RQ2 How does Lilypond recognition compare against other standard and custom formats?
RQ3 What conflicts currently prevent state-of-the-art models from further generalization?

2 BACKGROUND

2.1 Optical Music Recognition

TODO: OMR background

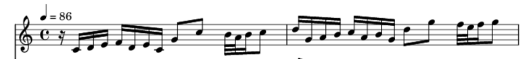
2.2 Lilypond

Lilypond was chosen for dataset file representation as it maintains accurate translation between digital (MIDI) and visual (image) notation systems [5]. In particular, translation from Lilypond to MIDI is trivial, and Lilypond provides a more intuitive representation of musical information compared to raw bytes of MIDI data. This notation language consists of multiple layers to separate score components:

- **Document level:** components related to page layout and high-level musical details, (number of instruments/tracks, score engraving information).
- **Music level:** components related to low-level musical details, (notes, rhythms, durations, key/time signatures, tempo).

At the document level, aspects of a score that stay mostly or completely constant throughout a piece are indicated by specific, indent-sensitive keywords. For example, the number of voices/instruments and respective number of staves are initialized with the $\backslash Voice$ and $\backslash context$ commands, while high-level musical information is initialized by commands such as $\backslash time$ for time signature, $\backslash key$ for key signature, and $\backslash tempo$ for performance speed in beats per minute.

At the music level, rhythmic musical symbols are notated according to their pitches and relative time duration. pitches are all characters a, b, c, d, e, f, g, r, where r is a "rest" meaning no pitch occurs. To ascend or descend in pitch beyond a single musical "octave," the $'$ and , characters are appended to indicate one or more octave ascendings or descendings, respectively. Pitches are also proceeded by a rhythmic value representing its duration in time. These values are typically powers of two, (but can technically be any positive floating-point value), and they dictate how long a pitch is played with respect to the piece's time signature. For example, a score with time signature = 2/4 indicates that each measure has two beats, and each beat is the length of a quarter note (hard-coded in the denominator). In this case, the line "$c4 \quad d4$" would represent two quarter (4) notes or a single measure in the provided time signature. Additionally, notes without defined durational values take on the previous note's duration in a line, so a series of equal-duration notes is represented by one durational value. Finally, separations between measures are made with "$|\%n$", marking the end of measure



```
trackBchannelB = \relative c {
        r16 c' d e f d e c g'8 c b32 a b16 c8
        | % 2
        d16 g, a b c a b g d'8 g f32 e f16 g8
        | % 3
}
```

Figure 1: Lilypond (.ly) code and rendering

n. Figure 1 compares the rendering of a single staff of music with its relative Lilypond notation. [1]

3 EXPERIMENT

3.1 CRNN Model

TODO: CRNN model The proposed Image-to-MIDI model is a toy implementation of Shi, et al.'s pioneering work in CRNNs [8].

3.2 Data Specfications

TODO: dataset specifics MIDI data used for this experiment has been narrowed down to strictly two-stave piano "inventions" by Johann Sebastian Bach [1] to maintain rhythmic and compositional uniformity. These works maintain relatively similar quantization schemes (rhythms and durations of notes), are short, and have several clear transcriptions for research, education, and entertainment purposes.

4 RESULTS

5 DISCUSSION

TODO: discussion

6 CONCLUSIONS

TODO: conclusions

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[1]The time signature C or "common-time" is another common way of writing 4/4.

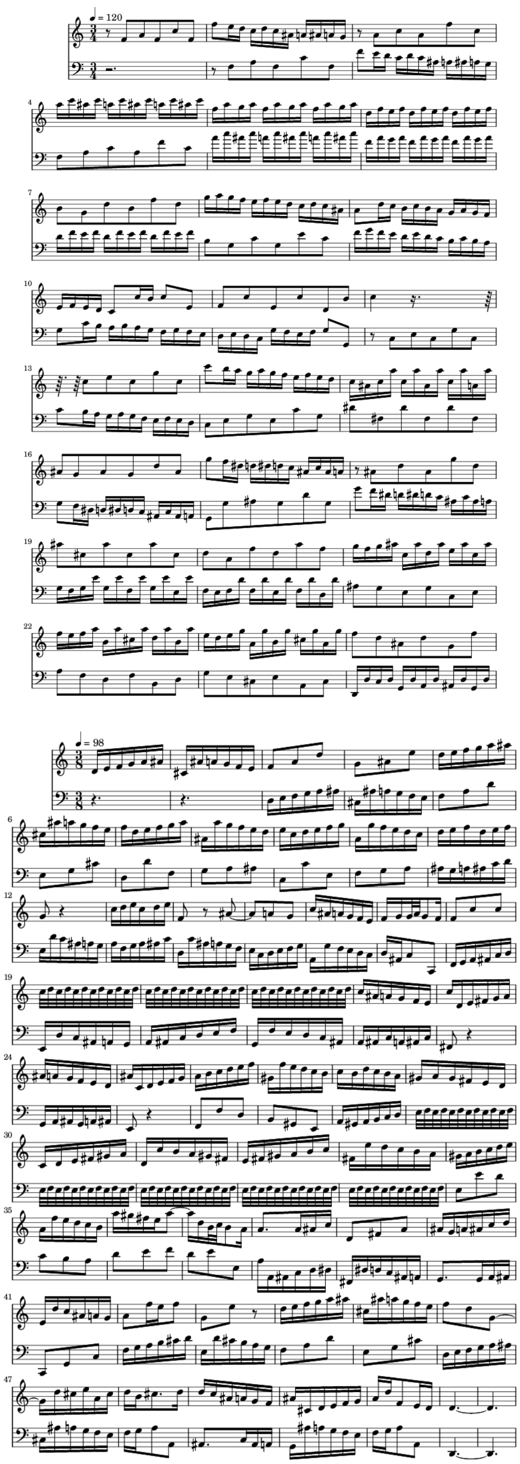

Figure 2: Excerpt of Invention No.4; cropped/prepared rendering of Invention No.8.

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