

# Optical Music Recognition for Homophonic LilyPond File Generation

Evan Matthews  
evanmm3@illinois.edu

University of Illinois Urbana-Champaign

## ABSTRACT

TODO: Abstract

### ACM Reference Format:

Evan Matthews. 2024. Optical Music Recognition for Homophonic LilyPond File Generation. In . ACM, New York, NY, USA, 3 pages. <https://doi.org/10.1145/nnnnnnn.nnnnnnn>

## 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.

### 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

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from [permissions@acm.org](mailto:permissions@acm.org).

Conference'17, July 2017, Washington, DC, USA

© 2024 Copyright held by the owner/author(s). Publication rights licensed to ACM.

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM

<https://doi.org/10.1145/nnnnnnn.nnnnnnn>

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 `\Voice` and `\context` commands, while high-level musical information is initialized by commands such as `\time` for time signature, `\key` for key signature, and `\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 preceded 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 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

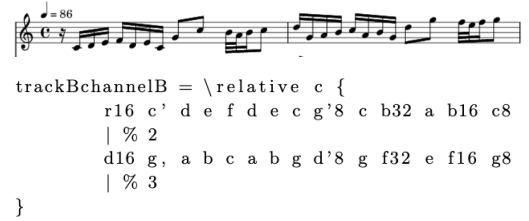


Figure 1: Lilypond (.ly) code and rendering

*n.* Figure 1 compares the rendering of a single staff of music with its relative Lilypond notation. <sup>1</sup>

## 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 Specifications

**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**

## REFERENCES

- [1] [n.d.]. Complete Bach Midi Index. <https://www.bachcentral.com/midiindexcomplete.html>
- [2] María Alfaro-Contreras, JoséM. Iñesta, and Jorge Calvo-Zaragoza. 2023. Optical music recognition for homophonic scores with neural networks and synthetic music generation. *International Journal of Multimedia Information Retrieval* 12, 1 (2023), 12. <https://doi.org/10.1007/s13735-023-00278-5>
- [3] Andrea, Paoline, and Amalia Zahra. 2021. Music note position recognition in optical music recognition using convolutional neural network. *International Journal of Arts and Technology* 13, 1 (2021), 45–60. <https://doi.org/10.1504/IJART.2021.115764>
- [4] Curtis Hawthorne, Andriy Stasyuk, Adam Roberts, Ian Simon, Cheng-Zhi Anna Huang, Sander Dieleman, Erich Elsen, Jesse Engel, and Douglas Eck. 2019. Enabling Factorized Piano Music Modeling and Generation with the MAESTRO Dataset. In *International Conference on Learning Representations*. <https://openreview.net/forum?id=r1IYRjC9F7>
- [5] Lilypond 2024. Lilypond music notation for everyone. <https://lilypond.org/doc/v2.25/Documentation/web/index>

<sup>1</sup>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.

- [6] Jirf Mayer, Milan Straka, Jan Hajič jr. au2, and Pavel Pecina. 2024. Practical End-to-End Optical Music Recognition for Pianoform Music. arXiv:2403.13763 [cs.CV]
- [7] Douglas Rakasiwi Nugroho and Amalia Zahra. 2024. Musical Note Position and Duration Recognition Model in Optical Music Recognition Using Convolutional Neural Network. *Journal of Image and Graphics* 12, 1 (Jan 2024), 32–39. <https://doi.org/10.18178/joig.12.1.32-39>
- [8] Baoguang Shi, Xiang Bai, and Cong Yao. 2015. An End-to-End Trainable Neural Network for Image-based Sequence Recognition and Its Application to Scene Text Recognition. arXiv:1507.05717 [cs.CV]
- [9] Aaron van den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew Senior, and Koray Kavukcuoglu. 2016. WaveNet: A Generative Model for Raw Audio. arXiv:1609.03499 [cs.SD]