Deep Learning Model for Identifying Artists of Fine Artwork

Paige Norris
Khoury College
Northeastern University
Portland, ME
norris.p@northeastern.edu

***Abstract*— To be filled in later. (*Abstract*)**

Keywords—component, formatting, style, styling, insert (*key words*)

I. Introduction (*Heading 1*)

Artistic expression has long been revered as a window into the human psyche, reflecting culture, emotion, and individuality. As the digital age unfolds, the intersection of art and technology presents new opportunities for understanding and appreciation. In this context, the task of identifying artists from their paintings has emerged as a fascinating challenge, blending art history with machine learning methodologies.

Artistic attribution presents a multifaceted challenge rooted in the complex interplay of style, technique, and historical context. Current methods for artist identification often rely on manual examination by art historians or rudimentary feature extraction algorithms, leading to subjective interpretations and limited scalability. The nuanced manifestations of artistic style, influenced by factors such as cultural milieu and personal idiosyncrasies, further complicate the task, requiring computational approaches capable of capturing subtle visual cues and contextual nuances.

Efficient and accurate artist identification holds significant implications for art scholarship, authentication, and provenance research, empowering stakeholders to gain deeper insights into art history and cultural evolution. By automating the process of identifying artists from their works, our proposed approach offers the potential to streamline archival efforts, facilitate art market transactions, and democratize access to cultural heritage. Moreover, by uncovering patterns and trends within artistic movements, our model may shed light on broader socio-cultural phenomena and aesthetic trends.

Existing approaches to artist identification encompass a spectrum of methodologies, from traditional connoisseurship techniques to computer vision algorithms. While manual attribution by art experts remains the gold standard in many cases, it is inherently subjective and labor-intensive. Computational methods, including feature-based classification algorithms and deep learning models, offer scalable alternatives but are often constrained by the complexity of artistic style and the availability of labeled training data.

Despite recent advancements, current approaches to artist identification face several limitations, including reliance on handcrafted features that may not fully capture the richness of artistic style, susceptibility to noise and variability in image data, and scalability issues associated with training deep learning models on large-scale art datasets. Moreover, the lack of standardized evaluation metrics and benchmark datasets hinders comparative analysis and model generalization across diverse artistic styles and periods.

To address these challenges, we propose a novel approach to artist identification using CNNs, which harness the power of deep learning to automatically extract hierarchical representations of artistic style from image data. By training our model on a curated subset of the WikiArt dataset, we aim to capture the subtle visual cues and stylistic nuances that distinguish individual artists, enabling accurate and scalable attribution of artworks. Through rigorous experimentation and evaluation, we demonstrate the efficacy and robustness of our approach, offering a promising avenue for advancing the field of computational art analysis.

II. Materials and Methods

A. Dataset

The WikiArt dataset is utilized in this study due to its depth and organization. The full dataset contains over 80 thousand pieces of artwork from 129 artists. It is comprised of images of artworks sourced from diverse artists, each artist contributing a distinct style to the collection. A smaller subset of roughly 8 thousand pieces from 10 artists was selected for the development of this model. It consists of ten subfolders, with each subfolder containing images exclusively from one artist. These images serve as the basis for training, testing, and validating the convolutional neural network (CNN) model.

B. Classes

The dataset encompasses artworks from ten different artists, each forming a distinct class for classification purposes. Each class represents the unique style and characteristics associated with the respective artist. The classes are not mutually exclusive, allowing the CNN model to recognize and categorize artworks according to their corresponding artists. Additionally, the classes are not balanced, reflecting the natural situation of some artists producing more work than others. For instance, the

Me, I'm paying this tuition.

Picasso class contains over 1,000 images, while the Arcimboldo class contains only 26.

C. Data Preprocessing

Prior to training the CNN model, several preprocessing steps were applied to the dataset to enhance model performance and facilitate effective learning. Firstly, the training, testing, and validation subsets were created for each class. Each class was separated into a train set containing 70% of the instance, a test set containing 20% of the instances, and a validation set containing 10% of the images. As the classes we non-uniform, the training, testing, and validation subsets are also unequal.

Secondly, the images were resized to a standardized dimension to ensure uniformity across the dataset. Next, data augmentation techniques, including random rotations, flips, and shifts, were employed to augment the dataset, thereby increasing its variability and improving the model's ability to generalize to unseen data.

Finally, normalization was performed to scale pixel values between 0 and 1, facilitating convergence during training.

D. CNN Model

The CNN model employed in this study was designed to classify artworks based on the style of the contributing artist. The architecture of the CNN comprises convolutional layers for feature extraction, followed by pooling layers for spatial downsampling. Subsequently, the extracted features are flattened and fed into fully connected layers for classification. Rectified Linear Units (ReLU) activation functions were used throughout the model to introduce non-linearity and improve its capacity to capture complex patterns. To prevent overfitting, dropout layers were incorporated, randomly dropping units during training. The model was trained using a categorical cross-entropy loss function and optimized using the Adam optimizer with default parameters. During training, the model's performance was evaluated using metrics such as accuracy, precision, recall, and F1-score, computed on both the training and validation datasets to assess its efficacy in artist classification.

III. Results

To be filled in later.

A. TBD

TBDTBDTBDD.

B. Units

- Use either SI (MKS) or CGS as primary units. (SI units are encouraged.) English units may be used as secondary units (in parentheses). An exception would be the use of English units as identifiers in trade, such as “3.5-inch disk drive”.
- Avoid combining SI and CGS units, such as current in amperes and magnetic field in oersteds. This often leads to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity that you use in an equation.
- Do not mix complete spellings and abbreviations of units: “Wb/m2” or “webers per square meter”, not “webers/m2”. Spell out units when they appear in text: “. . . a few henries”, not “. . . a few H”.
- Use a zero before decimal points: “0.25”, not “.25”. Use “cm3”, not “cc”. (*bullet list*)

C. Equations

The equations are an exception to the prescribed specifications of this template. You will need to determine whether or not your equation should be typed using either the Times New Roman or the Symbol font (please no other font). To create multileveled equations, it may be necessary to treat the equation as a graphic and insert it into the text after your paper is styled.

Number equations consecutively. Equation numbers, within parentheses, are to position flush right, as in (1), using a right tab stop. To make your equations more compact, you may use the solidus (/), the exp function, or appropriate exponents. Italicize Roman symbols for quantities and variables, but not Greek symbols. Use a long dash rather than a hyphen for a minus sign. Punctuate equations with commas or periods when they are part of a sentence, as in:

$$a + b = \gamma \tag{1}$$

Note that the equation is centered using a center tab stop. Be sure that the symbols in your equation have been defined before or immediately following the equation. Use “(1)”, not “Eq. (1)” or “equation (1)”, except at the beginning of a sentence: “Equation (1) is . . .”

D. Some Common Mistakes

- The word “data” is plural, not singular.
- The subscript for the permeability of vacuum μ_0, and other common scientific constants, is zero with subscript formatting, not a lowercase letter “o”.
- In American English, commas, semicolons, periods, question and exclamation marks are located within quotation marks only when a complete thought or name is cited, such as a title or full quotation. When quotation marks are used, instead of a bold or italic typeface, to highlight a word or phrase, punctuation should appear outside of the quotation marks. A parenthetical phrase or statement at the end of a sentence is punctuated outside of the closing parenthesis (like this). (A parenthetical sentence is punctuated within the parentheses.)
- A graph within a graph is an “inset”, not an “insert”. The word alternatively is preferred to the word “alternately” (unless you really mean something that alternates).
- Do not use the word “essentially” to mean “approximately” or “effectively”.
- In your paper title, if the words “that uses” can accurately replace the word “using”, capitalize the “u”; if not, keep using lower-cased.

- Be aware of the different meanings of the homophones "affect" and "effect", "complement" and "compliment", "discreet" and "discrete", "principal" and "principle".
- Do not confuse "imply" and "infer".
- The prefix "non" is not a word; it should be joined to the word it modifies, usually without a hyphen.
- There is no period after the "et" in the Latin abbreviation "et al.".
- The abbreviation "i.e." means "that is", and the abbreviation "e.g." means "for example".

An excellent style manual for science writers is [7].

IV. Using the Template

After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command, and use the naming convention prescribed by your conference for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper; use the scroll down window on the left of the MS Word Formatting toolbar.

A. Authors and Affiliations

The template is designed for, but not limited to, six authors. A minimum of one author is required for all conference articles. Author names should be listed starting from left to right and then moving down to the next line. This is the author sequence that will be used in future citations and by indexing services. Names should not be listed in columns nor group by affiliation. Please keep your affiliations as succinct as possible (for example, do not differentiate among departments of the same organization).

1) For papers with more than six authors: Add author names horizontally, moving to a third row if needed for more than 8 authors.

2) For papers with less than six authors: To change the default, adjust the template as follows.

a) Selection: Highlight all author and affiliation lines.

b) Change number of columns: Select the Columns icon from the MS Word Standard toolbar and then select the correct number of columns from the selection palette.

c) Deletion: Delete the author and affiliation lines for the extra authors.

B. Identify the Headings

Headings, or heads, are organizational devices that guide the reader through your paper. There are two types: component heads and text heads.

Component heads identify the different components of your paper and are not topically subordinate to each other. Examples include Acknowledgments and References and, for these, the correct style to use is "Heading 5". Use "figure caption" for your Figure captions, and "table head" for your table title. Run-in heads, such as "Abstract", will require you to apply a style (in this case, italic) in addition to the style provided by the drop down menu to differentiate the head from the text.

Text heads organize the topics on a relational, hierarchical basis. For example, the paper title is the primary text head because all subsequent material relates and elaborates on this one topic. If there are two or more sub-topics, the next level head (uppercase Roman numerals) should be used and, conversely, if there are not at least two sub-topics, then no subheads should be introduced. Styles named "Heading 1", "Heading 2", "Heading 3", and "Heading 4" are prescribed.

C. Figures and Tables

a) Positioning Figures and Tables: Place figures and tables at the top and bottom of columns. Avoid placing them in the middle of columns. Large figures and tables may span across both columns. Figure captions should be below the figures; table heads should appear above the tables. Insert figures and tables after they are cited in the text. Use the abbreviation "Fig. 1", even at the beginning of a sentence.

TABLE I. Table Type Styles

Table Head	**Table Column Head**		
	Table column subhead	***Subhead***	***Subhead***
copy	More table copy[a]		

We suggest that you use a text box to insert a graphic (which is ideally a 300 dpi TIFF or EPS file, with all fonts embedded) because, in an MSW document, this method is somewhat more stable than directly inserting a picture.

To have non-visible rules on your frame, use the MSWord "Format" pull-down menu, select Text Box > Colors and Lines to choose No Fill and No Line.

a. Sample of a Table footnote. (*Table footnote*)

Fig. 1. Example of a figure caption. (*figure caption*)

Figure Labels: Use 8 point Times New Roman for Figure labels. Use words rather than symbols or abbreviations when writing Figure axis labels to avoid confusing the reader. As an example, write the quantity "Magnetization", or "Magnetization, M", not just "M". If including units in the label, present them within parentheses. Do not label axes only with units. In the example, write "Magnetization (A/m)" or "Magnetization {A[m(1)]}", not just "A/m". Do not label axes with a ratio of quantities and units. For example, write "Temperature (K)", not "Temperature/K".

Acknowledgment *(Heading 5)*

The preferred spelling of the word "acknowledgment" in America is without an "e" after the "g". Avoid the stilted expression "one of us (R. B. G.) thanks ...". Instead, try "R. B. G. thanks...". Put sponsor acknowledgments in the unnumbered footnote on the first page.

References

The template will number citations consecutively within brackets [1]. The sentence punctuation follows the bracket [2].

Refer simply to the reference number, as in [3]—do not use “Ref. [3]” or “reference [3]” except at the beginning of a sentence: “Reference [3] was the first ...”

Number footnotes separately in superscripts. Place the actual footnote at the bottom of the column in which it was cited. Do not put footnotes in the abstract or reference list. Use letters for table footnotes.

Unless there are six authors or more give all authors’ names; do not use “et al.”. Papers that have not been published, even if they have been submitted for publication, should be cited as “unpublished” [4]. Papers that have been accepted for publication should be cited as “in press” [5]. Capitalize only the first word in a paper title, except for proper nouns and element symbols.

For papers published in translation journals, please give the English citation first, followed by the original foreign-language citation [6].

Alzheimer's disease (AD) is a chronic neurocognitive disease that mainly impacts older adults worldwide. With the progression of AD, the individuals experience memory and cognition issues, impacting their quality of life and those of their families.. According to the Alzheimer's Association [1, 2], approximately six million Americans are affected by Alzheimer's disease. This figure has increased by 16% during the current Covid-19 pandemic. Moreover, the likelihood of developing AD increases with age; it increases by 5.3% in those aged between 65 to 74 years old, 13.8% in those aged between 75 to 84 years old, and 34.6% in those aged 85 years old and older [1].
AD is thought to be caused by a buildup of proteins that interfere with brain communication. However, the exact mechanism of the cause is not well understood, and the buildup can occur well before symptoms finally appear [3]. This disease can be categorized into different stages based on cognitive function: cognitively normal (CN), early mild cognitive impairment (EMCI), significant memory concern (SMC), and late mild cognitive impairment (LMCI). CN refers to healthy individuals with no apparent symptoms. In EMCI, signs of AD start manifesting, including forgetting events and losing things, which usually prompts people to consult a physician [5]. SMC is the moderate stage of AD that is characterized by more frequent forgetting and decreased cognitive abilities. LMCI is the severe stage of the disease characterized by severe cognitive impairment requiring a caretaker [6].
Therefore, early detection could result in earliest treatment, slowed disease progression, and improved quality of life for the patient. An early diagnosis would provide the patient's family with enough time to make informed decisions and align care resources as needed. Several biomarkers and indicators are used for this diagnosis. For instance, Magnetic resonance imaging (MRI) can evaluate brain structures often affected by AD. Similarly, positron emission tomography (PET) scans use radiopharmaceutical markers to detect specific proteins involved in AD development. These proteins are located within the Cerebrospinal Fluid (CSF), which serves as another biomarker. Aside from cranial evaluation, cognitive tests also serve as a good progress measure of this disease. In addition, studies have identified some risk factors that are tightly related to developing AD, including age, gender, and a specific gene (i.e., Apolipoproteins 4 (APOE)) [7].
Several techniques have been proposed to detect and predict AD. Similar to other research areas, conventional machine learning and deep learning techniques have become popular tools for tackling this particular problem, as they provide multiple benefits, such as efficient data handling and improved performance. For instance, the authors in [8] used a graph convolutional network (GCN) model to predict AD and Autism disorders. This model consists of a sparse graph, where nodes are heavily associated with imaging-based feature vectors, and the phenotype data are integrated as edge weights. The evaluation of the proposed model is conducted using two large datasets, ADNI for predicting AD and ABIDE for predicting Autism. Simulation analysis of their proposed technique highlight an increase in accuracy for both disease predictions.
In [9], the authors proposed a deep and joint learning method to predict AD's longitudinal data. This study built a framework according to longitudinal time points to predict clinical scores. The proposed model is then formed using linear regression and support vector regression. Experiments were conducted using the ADNI dataset and demonstrated a strong relationship between clinical scores and MRI data performing315978-1-6654-8009-3/22/$31.00 ©2022 IEEE
2022 IEEE International Conference on Electro Information Technology (eIT) | 978-1-6654-8009-3/22/$31.00 ©2022 IEEE | DOI: 10.1109/eIT53891.2022.9813900

better than some other state-of-the-art studies in terms of prediction scores. In [10], the authors proposed an AD detection technique exploiting transfer learning and MRI scans. First, an image entropy technique is trained to find the most important slices of MRI images, then a layer-wise transfer learning to a Convolutional neural network (CNN) is employed. Results show a slight increase in the detection accuracy of different class labels. More recently, the authors of [11] proposed a detection technique based on multi-task learning for longitudinal data. The main objective of this model is to keep track of the relationships between different prediction tasks of cognitive scores. Their comparative performance analysis indicate that their proposed model provides minimum error predictions, even when considering a small longitudinal dataset.
Although these techniques have acceptable results, they have several limitations. For instance, there is no consensus on an optimal strategy to handle this problem. This is mainly due to the lack of comparative analysis between different previously proposed techniques. In addition, most of these studies employ a binary classification for AD detection and do not to consider its various stages (e.g., EMCI, LMCI), which can result in a partial diagnosis and an incomplete view of the disease’s current state. Motivated by these limitations, we propose a one-level multi-task deep learning technique that can detect AD and identify its stage. We perform hyper-parameter tuning to ensure the optimal set of input features and employ multiple metrics to assess the model performance.
The remainder of this paper is organized as follows: Section

II outlines the data and techniques employed for developing the multi-task deep AD detection model. Section III provides and discusses the simulation results. While section IV concludes the paper

[1] G. Eason, B. Noble, and I. N. Sneddon, “On certain integrals of Lipschitz-Hankel type involving products of Bessel functions,” Phil. Trans. Roy. Soc. London, vol. A247, pp. 529–551, April 1955. *(references)*

[2] J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[3] I. S. Jacobs and C. P. Bean, “Fine particles, thin films and exchange anisotropy,” in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.

[4] K. Elissa, “Title of paper if known,” unpublished.

[5] R. Nicole, “Title of paper with only first word capitalized,” J. Name Stand. Abbrev., in press.

[6] Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, “Electron spectroscopy studies on magneto-optical media and plastic substrate interface,” IEEE Transl. J. Magn. Japan, vol. 2, pp. 740–741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982].

[7] M. Young, The Technical Writer’s Handbook. Mill Valley, CA: University Science, 1989.