https://doi.org/10.2352/EI.2024.36.4.MWSF-342

DeepMammo: Deep Learning algorithm for Digital Mammogram Source Identification

Farid Ghareh Mohammadi[1,2]***, Ronnie Sebro*** [1,2]

1 : ***Department of Radiology, Mayo Clinic, Jacksonville, Fl, USA, 32224***
2 : ***Center for Augmented Intelligence, Mayo Clinic, Jacksonville, Fl, USA, 32224***
Emails : Gharehmohammadi.farid@mayo.edu, Sebro.ronnie@mayo.edu

Abstract

Advances in AI allow for fake image creation. These techniques can be used to fake mammograms. This could impact patient care and medicolegal cases. One method to verify that an image is original is to confirm the source of the image. A deep-learning algorithm(DeepMammo)-based on CNNs and FC-NNs, used to identify the machine that created any mammogram. We analyze mammograms of 1574 patients obtained on 7-different mammography machines and randomly split the dataset by patient into training/validation(80%) and test(20%) datasets. DeepMammo has an accuracy of 98.09%, AUC of 95.96% in the test dataset.

Keywords: *Deep Learning, Machine Learning, Radiology, Mammograms, Medical Imaging, Forensic Science*

Introduction

Artificial intelligence (AI) usage has increased over the past decade and is increasingly used in social media to generate fake or altered digital images and videos [1, 2]. AI has also been simultaneously utilized to identify digital images and videos that have been faked or altered [3, 4, 5, 6]. Fake digital images and videos have become an urgent threat in the digital world. Healthcare institutions use digitized images from various machines including radiograph machines, magnetic resonance imaging (MRI) scanners, computed tomography (CT) scanners, and mammogram machines. These machines create images of the human body that are utilized for diagnostic, screening and treatment purposes. The same techniques used to fake and alter digital images and videos in social media may eventually be used in healthcare with significant negative outcomes for patients, healthcare providers, and healthcare institutions. One method of determining whether a digital image is fake is determining whether the source of the image can be validated.

Source identification of medical images is important for several reasons. One is for image authentication and can help ensure the accuracy and reliability of the diagnostic process [7]. Imaging devices produce images with varying levels of quality, resolution, and artifacts. Identifying the source machine that created the image provides valuable information that can be used to understand the technical characteristics and properties of the image. Source identification can play a role in legal forensic investigations. In some cases, the origin of a medical image may become a subject of interest, such as when analyzing evidence for medical malpractice cases or in criminal investigations. By identifying the source machine, investigators can establish a link between the image and the specific equipment used.

However, source identification of medical images is not always a straightforward task [8]. Several factors contribute to the complexity of the problem. While some imaging systems may include device-specific information, it is not always consistently recorded or easily accessible. Additionally, medical images can undergo various post-processing steps, such as compression, resizing, or format conversions, which can further obscure the original source information. These alterations may be necessary for storage, transmission, or compatibility purposes, but they can complicate the process of source identification [4].

Efforts have been made to develop techniques for source identification of medical images [7, 9, 10, 11]. These methods often involve analyzing the image content, statistical properties, or machine-specific patterns to infer the source machine. Machine learning algorithms, such as deep neural network [4, 5], have shown promises in distinguishing images from different radiograph machine sources by learning patterns specific to each device. However, such techniques require large datasets with labeled images to train the models effectively. Researchers have also used deep learning algorithms to identify the magnetic resonance imaging (MRI) machine that created an image [12]. In this model, Fang et al. had an AI model with accuracy of 97.88% to identify which of two MRI manufacturers created a MRI image. Their AI model also had an accuracy of 91.07%) to differentiate 4 MRI models. They noted that their proposed deep learning algorithm (MISLnet) fails on unbalanced datasets.

Researchers created a deep learning algorithm (DeepRSI) with accuracy (ACC) of 98.54% and area under curve (AUC) of 97% to detect the radiographic machine manufacturer [4]. Gharehmohammadi and Sebro updated their initial results and showed that DeepRSI had an accuracy of 99.00% and AUC of 99% and 97.00% (AUC=94%) for identifying the source (manufacture and model) of foot radiographs, respectively [5].

In this research, we study mammography a completely different imaging modality from radiography and MRI. Our goal was to use deep learning to identify the mammography machine that produced a mammogram. Mammograms are the source of many medical-legal cases in radiology. Identifying the source of a mammogram image is important for several reasons.

Causation: Identifying the source of a mammograms is essential in determining whether a particular individual or entity is legally responsible for the harm suffered by a patient. For example, in a medical malpractice case, determining whether a healthcare provider's actions or negligence caused harm to a patient requires identifying the source of the mammograms. This is crucial because

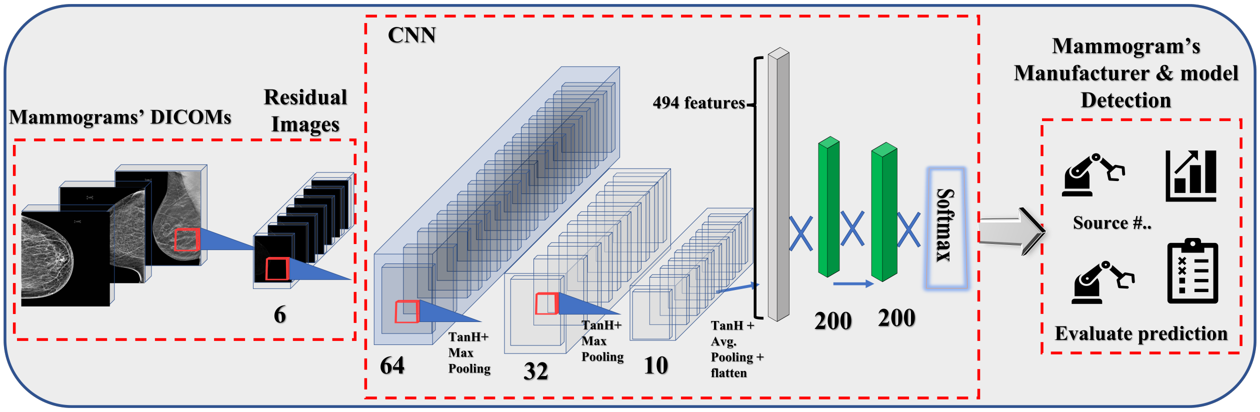

Figure 1: A general schema of DeepMammo for Mammogram's source identification

the detection of fake images is beyond the capability of most human experts [13].

Evidence: Proper mammogram source identification can provide critical evidence in a medical-legal case. Medical legal cases involve gathering medical records, expert testimony, laboratory results, and evaluation other data to establish a link between the source and the patient's condition.

In summary, source identification is a fundamental aspect of medical-legal cases as it helps establish causation, determine liability, provide evidence, and ultimately ensure that patients receive appropriate justice in cases of medical malpractice disputes.

Materials and Methodology

The main goal is to classify mammography images based on their unique sources. This paper introduces DeepMammo, an innovative content-free deep learning algorithm designed for mammogram source identification. The key innovation of DeepMammo lies in its capacity to differentiate mammograms originating from the same source but differing in physical location. DeepMammo utilizes convolutional neural networks (CNNs) where there are three convolutional layers followed by three fully connected neural networks(FCNNs). The details of the Steps 1 through Step 7 required to create DeepMammo which are presented in Algorithm 1.

Data Acquisition: Step 1

The dataset was derived from patients who underwent a mammography procedure at Mayo Clinic between 01/2020 and 01/2022. Mammograms were obtained using the HOLOGIC, Inc. [Selenia Dimensions] system based in Bedford, MA, USA. This introduces a unique challenge, as research studies typically seek to differentiate between distinct imaging machines. In our investigation, our objective is to identify specific radiographic machine manufacturers and models that only differ in physical location.

The dataset was randomly divided into two datasets: a training/validation dataset (n =1264 (5947) , 80%) and a test dataset (n = 310 (1322), 20%). This division was performed at the patient level, guaranteeing that there was no information leakage between dataset partitions.

The mammograms' manufacturers and models are provided in Table 1. The data was analyzed in accordance with the Health Insurance Portability and Accountability Act (HIPAA).

Mammography Protocols and Techniques

Mammography is a specialized medical imaging technique used to detect and diagnose breast cancer. It involves the use of low-dose X-rays to create high resolution detailed images of the breast tissue. Mammography protocols and techniques refer to the standardized procedures and approaches used to perform mammographic examinations, ensuring accurate and consistent images while minimizing patient radiation exposure.

Screening mammography is the routine examination of asymptomatic women with the goal of detecting breast cancer at an early, more treatable stage. It involves taking two X-ray images of each breast in different projections: the craniocaudal (CC), *C*_View and the mediolateral oblique (MLO), MLO_view. These projections provide different perspectives of the breast tissue, improving the chances of detecting abnormalities. We used only screening mammography images.

Image Processing: Step 2-3

In Step 2: Mammograms are downloaded in Digital Imaging and Communications in Medicine (DICOM) format, a widely used format for medical imaging data. The mammograms were converted into the Portable Network Graphic (PNG) format to ensure consistent image dimensions and intensity values. To standardize the pixel intensities across the mammograms, a transformation was applied. This transformation involved re-scaling the intensity values within the range of 0 to 255. All mammograms in PNG format were then uniformly resized to 256x256 pixels dimensions to maintain uniformity in image representation. This resizing operation ensured that all mammograms had the same image size which is important for deep learning models that require fixed input dimensions.

Balancing batches : Step 3: We filtered out classes with less than 200 distinct patients to make the dataset with enough samples of class for training and validation. We ended up with seven different mammogram machines (classes). We use a balancing function to randomly choose samples from each class to balance the number of batches per each class to let the deep learning model learn from balanced data batches. We provide the same condition for each class to feed into the model to learn and predict the classes.

Deep Learning Architecture: Steps 4-6

DeepMammo uses initial layer called *layer 0* in which we aim to extract the content-free(noise) pixels from mammograms. This layer also is known as error feature prediction layer [3] where is

Algorithm 1 DeepMammo: mammograms source identification pseudo code. (hyperbolic tangent function: Tanh)

Input: Mammograms' DICOMs
Begin
Step 1: Divide datasets randomly by patient into training/validation (80%) and test (20%)
Step 2: Read mammograms in DICOMs format and convert them to PNG format image. — Data pre-processing and handling
Step 3: Balancing batches: Distribute stratified unbalanced data classes into batches
Step 4: Error feature prediction
  Conv. layer 0: Generate low-level features, 6 filters (7x7), padding=2 — Content-free pixels (Residual Images)
  Normalize the filter and set the center equal to -1 for all 6 filters
Step 5: Convolutional Neural Networks (CNNs)
  Conv. layer 1: 64 filters(7x7), stride=2, padding=3, maxPooling=3, activation function= Tanh
  Conv. layer 2: 32 filters(7x7), stride=2, padding=2, maxPooling=3, activation function = Tanh — Extracting high-level features
  Conv. layer 3: 10 filters(1x1), stride =2, padding=0, Avg.Pooling=3, activation function = Tanh
Step 6: Fully Connected Neural Networks (FCNNs)
  FCNN. layer 1: 200 nodes, activation function = Tanh
  FCNN. layer 2: 200 nodes, activation function = Tanh — Learning a model for source identification
  FCNN. layer 3: classes, activation function = softmax
Step 7: Evaluate the performance of DeepMammo
End

responsible to ignore the content pixels and focus on the accumulative noise that are traceable. The whole noise pixels exist in images called fingerprints that play a main role in DeepMammo to distinguish mammography machines. These fingerprints are the pattern in the noise pixels and are distinctly different between images obtained from different mammogram machines.

Step 5 starts with CNN layers in which we learn from low-level features to generate a model based on the pattern found in the features (noise pixels). We have three light layers with 64, 32 and 10 filters used chronologically in the layers followed by the hyperbolic tangent function(Tanh) activation function (Elaborated in Algorithm 1).

We train a model using the high-level features extracted in step 5. We use two hidden layers with 200 nodes each used Tanh function to regulate the weights. DeepMammo ends with the output layer, using the softmax function, and generates a prediction probability of the source of mammograms.

In our training process, we employ a cross-entropy function to minimize prediction errors, aiming to optimize prediction accuracy performance. It is noteworthy that no augmentation data were utilized in the training dataset.

Performance Evaluation: Step 7

To assess the effectiveness of our method, six key performance metrics are employed: accuracy (ACC), area under the receiver operating characteristic curve (AUC), precision or positive predictive value (PPV), negative predictive value (NPV), specificity (SPE), and sensitivity (SEN) or recall.

Computational Resource

DeepMammo was developed using Python (version 3.10.8), a widely adopted programming language for machine learning and deep learning applications. The algorithm leveraged key deep learning dependencies, including PyTorch (version 1.13.1), Torch (version 1.13.1), and PyTorch-CUDA (version 11.7). These libraries provided essential tools, frameworks, and functionalities for constructing and training the deep neural network architecture.

The analysis was performed using NVIDIA Quadro RTX 4000 GPU, equipped with 8 GB of dedicated video memory (DRAM), and 32 GB of shared GPU memory. In addition to the GPU, the machine utilized an Intel® Xeon® W-2123 3.60 GHz central processing unit (CPU). The CPU provided strong single-threaded performance, capable of handling various non-parallel tasks efficiently. Furthermore, the machine boasted 64 GB of random-access memory (RAM), enabling the storage and retrieval of data during training and inference processes.

The availability of these computational resources, including the powerful GPU, robust CPU, and ample RAM, played a crucial role in facilitating the execution and evaluation of the DeepMammo for source identification of the mammograms. These resources allowed for efficient utilization of parallel processing capabilities, enabling faster training times and more effective model evaluation.

Experimental Results

DeepMammo was able to identify the source of mammography machines using mammograms DICOMs with high accuracy and high AUC . We collected mammograms at Mayo Clinic and performed all steps stated for DeepMammo in Algorithm 1. We use the reported metrics for assessing test dataset.

In this dataset, we analyzed CC and MLO screening mamographs of both left and right breasts.

We examined the finger prints recorded in the images. The performance results of DeepMammo stated in Table 2. Two of the seven mammography machines (class 3 and 6) created fingerprints that were sufficiently robust that DeepMammo could be used to perfectly identify these mammography machines without error.

By implementing these pre-processing procedures, the study aimed to create a standardized and consistent dataset for subsequent analysis.

Discussion

This study uses a deep learning algorithm to enable the rapid and accurate mammography machine that was used to create a mammogram image. The trained model used high-level features in the

Table 1: Mammgraphy machine Manufacturer and model distributions in the craniocaudal (CC) and mediolateral oblique (MLO)

Classes	Manufacturer	Models	Mammography Protocols	Total Patients (Images)	Training/Validation Patients (Images)	Test Patients (Images)
0	HOLOGIC, Inc.	Selenia Dimensions	CC and MLO	241 (1049)	193 (839)	48 (210)
1	HOLOGIC, Inc.	Selenia Dimensions	CC and MLO	206 (912)	165 (729)	41 (183)
2	HOLOGIC, Inc.	Selenia Dimensions	CC and MLO	209 (1006)	168 (804)	41 (202)
3	HOLOGIC, Inc.	Selenia Dimensions	CC and MLO	210 (976)	169 (780)	41 (196)
4	HOLOGIC, Inc.	Selenia Dimensions	CC and MLO	221 (1026)	178 (820)	43 (206)
5	HOLOGIC, Inc.	Selenia Dimensions	CC and MLO	222 (1060)	178 (848)	44 (212)
6	HOLOGIC, Inc.	Selenia Dimensions	CC and MLO	267 (1240)	215 (992)	52 (248)
Total:7	1(distinct)	1 (distinct)	2 (distinct)	1574 (7269)	1264 (5947)	310 (1322)

Table 2: Mammography machine Manufacturer and model identification

Classes	ACC (%)	AUC(%)	PPV(%)	NPV(%)	SPE(%)	SEN(%)
0	99.34	99.61	95.92	**100.00**	99.22	**100.00**
1	97.35	91.93	94.29	97.75	99.24	84.62
2	97.68	96.49	88.10	99.23	98.10	94.87
3	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
4	95.70	89.52	87.18	96.96	98.08	80.95
5	96.03	92.84	84.44	98.05	97.30	88.37
6	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
Total Average:	98.09	95.96	93.09	98.91	98.88	93.05

conten-free pixels of a mammogram extracted from convolutional layers. These patterns are fingerprints - distinct and specific to each mammography machine.

The proposed solution has the following advantages and disadvantages:

Clinical implications: the study's findings could have far-reaching practical implications across multiple domains, ranging from solving crimes and verifying media authenticity to improving healthcare diagnostics and enhancing the quality of visual content in various industries.

Forensic science media and authenticity verification: In an era of fake news and manipulated media, specialists can benefit from improved image analysis techniques to verify the authenticity of visual content. This is essential for maintaining the integrity of patient care and preventing the spread of misinformation.

Data security and image authentication: Beyond medial diagnosis, the study's findings can be applied in cybersecurity to verify the authenticity of images, preventing the use of manipulated or forged images in various online contexts. In the field of medicine, image data is crucial for diagnoses and treatment planning. Advancements in image analysis can lead to more accurate diagnoses and personalized treatment options for patients.

Limitations: While the deep learning algorithm for mammogram's source identification shows high performance, there are certain limitations that should be considered. We only had one single mammography manufacturer and only corresponding single model. Other mammographic machine manufacturers and models may be easier or more difficult to detect. DeepMammo's performance was robust enough to differentiate these mammographic machines from each other.

Limited Adoption and Implementation: This work has accomplished in an offline environment where we learn the deep learning model on a local system. The successful integration of the algorithm into routine clinical practice requires addressing practical challenges, such as computational resource requirements, compatibility with existing systems interfaces. These factors can impact the algorithm's adoption and widespread implementation.

Future works: This study opens up avenues for future research and development. Investigating the applicability of transfer learning techniques can be valuable. By leveraging pre-trained models on large-scale datasets, the algorithm can potentially benefit from learned features and patterns, leading to improved performance even with limited data.

Domain Adaptation: Since the algorithm's performance may vary when applied to unseen sources or different imaging protocols, future research can focus on domain adaptation techniques. Developing methods to adapt the algorithm to the other mammography protocols of imaging domains that enable us to enhance models ability to generalize and handle real-world variations.

Conclusion

In conclusion, this study used the content-free pixels to accurately identify the machine that created a mammogram.

Through extensive experimentation and analysis, the study has yielded important findings and implications.

The DeepMammo showcased promising performance in accurately categorizing mammograms based on their source. By leveraging the power of deep neural networks, the algorithm demonstrated high accuracy, AUC and robustness in distinguishing mammograms originating from different physical sources, including various imaging devices and facilities.

The results of this study have significant clinical implications. Accurate source identification of mammograms is crucial for patient care and medical legal challenges over time. The deep learning algorithm can aid in automating the source identification process, saving time and effort for image validation by radiologists.

The algorithm's effectiveness was evaluated on a dataset encompassing mammograms from different types of mammography screening techniques(CC and MLO). DeepMammo exhibited remarkable performance across a range of mammogram types, densities, and imaging protocols. This indicates its potential for broad applicability and generalizability in real-world clinical settings.

References

[1] H. Ali, S. Murad, and Z. Shah, "Spot the fake lungs: Generating synthetic medical images using neural diffusion models," in *Irish Conference on Artificial Intelligence and Cognitive Science*. Springer, 2022, pp. 32–39.

[2] Y. Cai, X. Hu, H. Wang, Y. Zhang, H. Pfister, and D. Wei, "Learning to generate realistic noisy images via pixel-level noise-aware adversarial training," *Advances in Neural Information Processing Systems*, vol. 34, pp. 3259–3270, 2021.

[3] B. Bayar and M. C. Stamm, "Constrained convolutional neural networks: A new approach towards general purpose image manipulation detection," *IEEE Transactions on Information Forensics and Security*, vol. 13, no. 11, pp. 2691–2706, 2018.

[4] F. Ghareh Mohammadi and R. Sebro, "Deep-rsi: Deep learning for radiographs source identification," in *2022 International conference on computational science and computational intelligence (CSCI)*. IEEE, 2022, pp. 1491–1496.

[5] ——, "Radiograph manufacturer and model identification using deep-rsi," in *European Conference on Cyber Warfare and Security*, vol. 22, no. 1, 2023, pp. 199–206.

[6] A. Ghai, P. Kumar, and S. Gupta, "A deep-learning-based image forgery detection framework for controlling the spread of misinformation," *Information Technology & People*, 2021.

[7] O. M. Al-Qershi and B. E. Khoo, "Passive detection of copy-move forgery in digital images: State-of-the-art," *Forensic science international*, vol. 231, no. 1-3, pp. 284–295, 2013.

[8] M. C. Stamm, M. Wu, and K. R. Liu, "Information forensics: An overview of the first decade," *IEEE access*, vol. 1, pp. 167–200, 2013.

[9] D. P. Chowdhury, S. Bakshi, P. K. Sa, and B. Majhi, "Wavelet energy feature based source camera identification for ear biometric images," *Pattern Recognition Letters*, vol. 130, pp. 139–147, 2020.

[10] L. Bondi, L. Baroffio, D. Güera, P. Bestagini, E. J. Delp, and S. Tubaro, "First steps toward camera model identification with convolutional neural networks," *IEEE Signal Processing Letters*, vol. 24, no. 3, pp. 259–263, 2016.

[11] X. Zhao and M. C. Stamm, "Computationally efficient demosaicing filter estimation for forensic camera model identification," in *2016 IEEE international conference on image processing (ICIP)*. IEEE, 2016, pp. 151–155.

[12] S. Fang, R. A. Sebro, and M. C. Stamm, "A deep learning approach to mri scanner manufacturer and model identification," *Electronic Imaging*, vol. 2020, no. 4, pp. 217–1, 2020.

[13] F. Palmiotto, "Detecting deep fake evidence with artificial intelligence: A critical look from a criminal law perspective," *Available at SSRN 4384122*, 2023.

Farid Ghareh-Mohammadi, Ph.D., is a postdoctoral fellow at Mayo Clinic, specializing in the exploration of Deep-Learning applications within the realm of real-world musculoskeletal imaging, focusing on both diagnosis and authentication. His Ph.D. in computer science with a concentration in meta-learning and multi-model classification is from University of Georgia. He published over 30 journal, conference papers and book chapters. He received the Outstanding Achievement Award for deep-learning at CSCI'19. He is the Associate Editor for CSCE'22-23.

Ronnie A. Sebro, M.D., Ph.D., is an internationally-renowned statistician, geneticist and musculoskeletal radiologist. His research focuses on using artificial intelligence and machine learning to improve diagnosis osteoporosis, sarcomas and other tumors, and other musculoskeletal conditions. He has published over 100 scientific journal papers and lectured nationally and internationally. He is the Deputy Editor of Radiology: Artificial Intelligence, Associate Editor for BMC Musculoskeletal Disorders, and Associate Editor for the Journal of Digital Imaging.