Mapping Cost-Sensitive Learning for Imbalanced Medical Data: Research Trends and Applications

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Keywords: Machine Learning, Data Imbalance, Cost-Sensitive Learning, Medical Data, Systematic Mapping Study.

Abstract: Incorporating Machine Learning (ML) in medicine has opened up new avenues for leveraging complex medical data to enhance patient outcomes and advance the field. However, the imbalanced nature of medical data poses a significant challenge, resulting in biased ML models that perform poorly on the minority class of interest. To address this issue, researchers have proposed various approaches, among which Cost-Sensitive Learning (CSL) stands out as a promising technique to improve the accuracy of ML models. To the best of our knowledge, this paper presents the first systematic mapping study on CSL for imbalanced medical data. To comprehensively investigate the scope of existing literature, papers published from January 2010 to December 2022 and sourced from five major digital libraries were thoroughly explored. A total of 173 papers were selected and analyzed according to three classification criteria: publication years, channels and sources; medical disciplines; and CSL approaches. This study provides a valuable resource for researchers seeking to explore the current state of research and advance the application of CSL for imbalanced data in medicine.

1 INTRODUCTION

Medicine is a dynamic and intricate field that has witnessed remarkable progress in recent decades, attributed to the advances in technology and medical imaging (Johnson et al., 2018). These developments have endowed healthcare providers with powerful tools, improving patient outcomes and extending life expectancies. Nevertheless, with the escalating complexity and abundance of medical data, medical practitioners now face new challenges in accurately diagnosing and treating patients.

To address these challenges, Machine Learning (ML), a branch of artificial intelligence, has emerged as a promising solution in recent years. ML techniques enable the analysis of massive amounts of data, recognizing patterns, and predicting outcomes. Consequently, it has opened up new perspectives into the fundamental disease mechanisms, ultimately facilitating improved healthcare delivery systems and more effective treatments and therapies. Additionally, ML harbours a tremendous potential to transform medical research, potentially unlocking novel discoveries and revolutionizing the field.

However, medical data is often imbalanced, meaning one class is underrepresented compared to the other. For instance, in cancer screening, the number of patients with cancer is typically much smaller than that of healthy patients. This data imbalance can lead to biased ML models that perform poorly on the minority class, which is more often than not the class of interest. ML researchers proposed various approaches to address this issue, including resampling (Khushi et al., 2021) and Cost-Sensitive Learning (CSL) (Elkan, 2001).

Resampling techniques aim to balance the data either by oversampling the minority class or undersampling the majority class. While resampling can enhance models' performance, it may result in overfitting or information loss (Hu et al., 2021). On the other hand, CSL tackles the class imbalance problem without any data modifications by assigning different misclassification costs to each class. In particular, cost-sensitive methods assign higher costs

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Araf, I., Idri, A. and Chairi, I.
Mapping Cost-Sensitive Learning for Imbalanced Medical Data: Research Trends and Applications.
DOI: 10.5220/0012176000003598
In *Proceedings of the 15th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2023) - Volume 1: KDIR*, pages 265-272
ISBN: 978-989-758-671-2; ISSN: 2184-3228

for misclassifying examples of the minority class and seek to minimize the high-cost errors (López, Fernández, García, Palade, & Herrera, 2013). This approach is advantageous in many real-world applications, including medical ones, where certain misclassifications can have more severe consequences (Sterner, Goretzko, & Pargent, 2021). For example, misclassifying a patient with cancer as healthy is more detrimental than the opposite, as it can delay treatment and lead to further complications. The misclassification costs are often specified as cost matrices, which can be expert-defined or estimated from training data (Fernández et al., 2018).

CSL techniques can be broadly classified into direct approaches and meta-learning approaches (Fernández et al., 2018; Liu et al., 2021). The former modify the learning algorithms by incorporating misclassification costs during the model training phase (Fernández et al., 2018). Conversely, the latter do not alter the learning algorithms per se (Liu et al., 2021). Instead, meta-learning approaches adjust the training data (preprocessing) or the model's outputs (postprocessing) to ensure cost sensitivity. Popular preprocessing techniques include instance weighting based on a cost matrix and MetaCost (Fernández et al., 2018), which relabels the training data according to misclassification costs. Postprocessing techniques, meanwhile, often involve adjusting the decision thresholds based on the pre-defined costs (Fernández et al., 2018; Liu et al., 2021).

Despite the potential of CSL in medical research, existing reviews on the topic (Freitas, Brazdil, & Costa-Pereira, 2009; Sterner et al., 2021) suffer from limitations, including a lack of systematic approach, limited scope or outdatedness. As such, a Systematic Mapping Study (SMS) was conducted to address CSL for imbalanced medical data, which, to the best of our knowledge, is the first of its kind. The contributions of this paper are two-fold. Firstly, a systematic and comprehensive overview of the current state of research on CSL for imbalanced data in the medical field is presented. Secondly, the existing literature's strengths and limitations are critically evaluated, and potential future research directions are suggested. To comprehensively investigate the scope of existing literature, materials from January 2010 to December 2022 were extensively explored. The materials were sourced from five major digital libraries: PubMed, ScienceDirect, IEEE Xplore, SpringerLink, and Google Scholar. The 173 selected papers were subsequently analyzed to answer three Mapping Questions (MQs): (i) publication years, channels and sources, (ii) medical disciplines, and (iii) CSL approaches.

The remainder of this paper is structured as follows. Section 2 details the research methodology. Section 3 reports the results of this study and provides an in-depth discussion of the findings, highlighting trends, strengths and gaps in the existing literature. Finally, Section 4 concludes the paper by summarising the main findings and outlining future work.

2 METHODOLOGY

An SMS systematically categorizes and classifies existing research in a particular field and often gives a visual summary of its results (Petersen, Feldt, Mujtaba, & Mattsson, 2008). It aims to determine the scope and extent of existing research on a topic, identify gaps and trends, and provide a foundation for future research. The present study follows the mapping process proposed by Peterson, Vakkalanka, and Kuzniarz (2015). This process covers: (i) clearly defining the research questions, (ii) developing a comprehensive search strategy to identify relevant papers, (iii) screening the identified papers based on inclusion and exclusion criteria, (iv) designing a classification scheme, and (v) data extraction and analysis, resulting in a systematic map.

2.1 Mapping Questions

This study aims to provide an overview and a structured understanding of the existing literature on using CSL for imbalanced medical data by addressing three MQs:

MQ1: In which years, publication channels and sources were the selected papers published?

MQ2: In which disciplines of medicine was CSL mainly employed?

MQ3: Which CSL approaches were most frequently used in medicine?

2.2 Search Strategy

The search is conducted in five digital libraries: PubMed, ScienceDirect, IEEE Xplore, SpringerLink and Google Scholar from January 2010 until December 2022. These libraries were chosen based on their extensive coverage of peer-reviewed publications in medicine and health sciences, as well as computer science and engineering.

The search string was formulated based on the principal terms from the MQs, as well as the PICO (Population, Intervention, Comparison and

Outcomes) framework (Kitchenham & Charters, 2007). Note that the third and fourth letters of PICO were not included in the search string formulation since neither empirical comparison nor measurable outcomes were considered in this study. Additionally, the search string was expanded to include alternative spellings and synonyms of the derived terms to ensure a comprehensive search.

The main search terms were initially linked with their substitutes using the Boolean operator "OR" and were joined using "AND" afterwards. The complete search string was defined as follows:
(Health* OR Medic* OR Disease OR Clinic*) AND ("Machine Learning" OR "Deep Learning" OR Intelligen* OR Classif* OR Predict* OR Diagnos* OR Prognos*) AND (Technique OR Method OR Tool OR Model OR Algorithm OR Approach OR Framework) AND ("Cost sensitive" OR Cost-sensitive OR "weighted cost function" OR "weighted loss function" OR "class weighting" OR re-weighting) AND (Imbalance* OR unbalance* OR "skewed class distribution" OR under-represented OR "majority class" OR "minority class").

2.3 Study Selection

The Inclusion Criteria (IC) and Exclusion Criteria (EC) used to identify the relevant papers are presented below.

IC1: Studies developing new or using existing cost-sensitive techniques in medicine.

IC2: Papers focusing mainly on cost-sensitive models in medicine, whether or not comparing them to other balancing techniques.

IC3: Papers presenting fair comparisons of several balancing techniques in medicine, including cost-sensitive methods.

IC4: Papers presenting comparisons between CSL methods in medicine without proposing any newly developed techniques.

IC5: Papers providing an overview of studies investigating cost-sensitive methods in medicine.

IC6: Papers combining cost-sensitive methods with other balancing techniques in medicine.

EC1: Papers published earlier than January 2010 or later than December 2022.

EC2: Papers using several datasets from multiple areas with a mere presence of medical ones.

EC3: Papers using cost-sensitive techniques in public health, biology, pharmacology or genomics.

EC4: Papers available as abstracts, posters, book chapters, or presentations.

EC5: Non-peer-reviewed papers.

EC6: Duplicate publications of the same study.

EC7: Studies published in languages other than English.

EC8: Short papers.

EC9: Papers for which the full texts are not available.

The suitability of a study for inclusion was determined by examining its title, abstract, and keywords. All the articles were further screened by reviewing their introduction, discussion, and conclusion sections. Full-text reading was conducted in case of doubt. Initially, one author examined the papers, and the remaining authors subsequently evaluated the final selection.

Furthermore, each paper was evaluated by two authors based on a set of Quality Assessment (QA) criteria to ensure that the selected studies are of sufficient quality and provide reliable and valid evidence to address the MQs. The criteria included clear empirical results, justified empirical design, performance evaluation, comparison with other methods, explicit presentation of benefits and limitations, and publication in a recognized source.

2.4 Data Extraction Strategy and Synthesis

During this phase, a data extraction form was used for each selected paper to answer the MQs.

MQ1: Publication years, channels (journal, conference or workshop), and sources were extracted to address this question.

MQ2: Each paper was examined to determine its specific medical focus, encompassing disciplines such as oncology, cardiology, ophthalmology, and others, as detailed exhaustively in ("Specialty Profiles | Careers in Medicine," 2023).

MQ3: The proposed cost-sensitive methods in the selected studies were identified. These methods can be classified as either direct or meta-learning approaches. The latter could further be classified as preprocessing or postprocessing methods (Fernández et al., 2018).

3 RESULTS AND DISCUSSION

This section provides an overview of the study selection. It also presents and discusses the mapping results according to the proposed MQs.

3.1 Study Selection

Figure 1 displays the number of articles at each stage of the selection process. Initially, 49325 candidate papers were identified, from which 49124 studies were discarded according to the IC and EC.

28 studies that did not fulfil the QA criteria were later excluded. Eventually, 173 papers were retained to answer the MQs. Given space limitations, the list of selected papers and their extracted data can be obtained through an email request to the authors.

3.2 MQ1: In Which Years, Publication Channels and Sources Were the Selected Papers Published?

Figure 2 shows the number of selected studies per publication channel from January 2010 to December 2022. Three main channels were identified: journals, conferences and workshops. Out of the 173 selected studies, the majority, precisely 69.9% (121 papers), were published in journals, 27.2% (47 papers) were published in conference proceedings, and only 2.9% (five papers) were published in workshops. Table 1 outlines the publication sources that have published more than two papers.

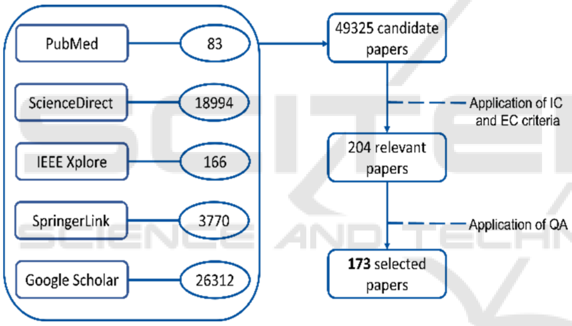

Figure 1: Selection process.

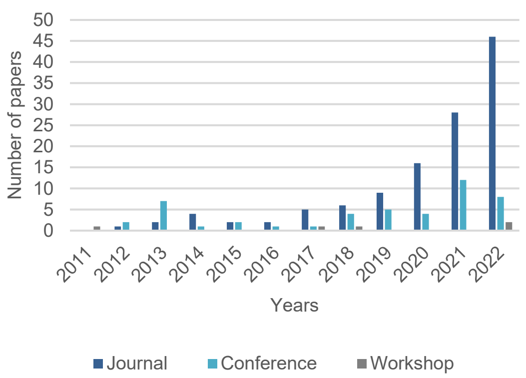

Figure 2: Distribution of the selected papers per publication year and channel.

Table 1: Publication sources.

Journal source	No. Papers	Percentage
Computer Methods and Programs in Biomedicine	9	5.2%
Computers in Biology and Medicine	8	4.6%
BMC Medical Informatics and Decision Making	5	2.9%
Neurocomputing	5	2.9%
Multimedia Tools and Applications	5	2.9%
Medical Image Analysis	4	2.3%
Biomedical Signal Processing and Control	4	2.3%
Artificial Intelligence in Medicine	3	1.7%
Applied Soft Computing	3	1.7%
Other	75	43.4%
Conference source	No. Papers	Percentage
International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI)	5	2.9%
Other	42	24.3%
Workshop source	No. Papers	Percentage
International Workshop on Machine Learning in Medical Imaging (MLMI)	2	1.7%
Other	2	1.2%

The findings indicate that Computer Methods and Programs in Biomedicine was the most commonly targeted journal venue, while the International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI) and the International Workshop on Machine Learning in Medical Imaging (MLMI) emerged as the most frequently occurring sources for conference and workshop papers, respectively.

Chronologically speaking, conference papers were the dominant publication type in 2012 and 2013. However, the trend shifted in 2014 as the journal publication frequency surpassed that of conference papers in subsequent years. A key observation is that the gap between the two types of publications became increasingly pronounced from 2020 onwards. The analysis further revealed a growing trend of publications, particularly since 2020, when the count peaked significantly. Notably, no study was published in 2010, and only one workshop paper was published in 2011.

The dearth of published papers in 2010-2011 and the dominance of conference papers until 2013 suggest that CSL research in the medical field was in its early stages. However, as the field progressed, researchers started prioritizing top-tier journals due to their strict review processes and higher publication standards, resulting in more rigorous research. This shift towards journal publications began in 2014 when the number of journal articles surpassed conference papers and continued to widen in subsequent years. This trend indicates a maturing field and researchers increasingly meeting the demanding standards of high-quality journals.

The growing interest and abundance of publications on CSL can be attributed to several key factors. Firstly, the development of high-throughput technologies has resulted in massive amounts of medical data (Johnson et al., 2018), including clinical data, electronic health records, and data from wearable devices. These advancements in data collection have created an urgent need for novel methods to analyze and leverage this data for improved medical outcomes. Secondly, the inherent imbalanced nature of this collected data poses a critical challenge that impacts the accuracy and reliability of ML models in medical applications. Thirdly, the significant advances in CSL algorithms (Khan, Hayat, Bennamoun, Sohel, & Togneri, 2018) and their success in other fields (Sahin, Bulkan, & Duman, 2013) have encouraged researchers to apply these techniques in the medical domain, where they are much needed. Additionally, the advances in deep learning have been a significant catalyst for progress in medical data analysis (Esteva et al., 2019). Finally, the increasing availability of public datasets and tools for analyzing medical data has facilitated the dissemination and replication of research findings. As a result, the research community has become more aware of the importance of addressing the class imbalance problem, leading to a surge in publications on this topic, particularly in recent years.

Besides, the findings revealed diverse publication sources covering various disciplines such as medicine, medical informatics, computer science, and artificial intelligence. This diversity reflects the interdisciplinary nature of the research topic, requiring a multi-faceted approach that draws on expertise from different fields.

3.3 MQ2: In Which Disciplines of Medicine Was CSL Mainly Used?

The 173 selected studies collectively explored 21 distinct medical disciplines. Interestingly, 17 papers addressed more than one discipline, either by investigating a topic at the intersection of two medical sub-fields (e.g., (Sung, Hung, & Hu, 2021)) or by testing their methods on a diverse range of disciplines (e.g., (Gan, Shen, An, Xu, & Liu, 2020)). Figure 3 showcases the distribution of studies per medical sub-field, focusing solely on sub-fields addressed by at least 2% of the selected papers.

The findings revealed that oncology is the most extensively studied discipline, accounting for 31.2% (54 papers) of the selected studies. As per the World Health Organization (WHO), cancer is a leading cause of mortality globally, accounting for approximately 10 million deaths in 2020 alone ("Cancer," 2020). The significance of accurate and timely diagnosis and treatment is paramount, and ML techniques hold great promise in this regard. However, cancer is a highly heterogeneous disease that can manifest differently in each patient. Additionally, patients often present with complex medical histories and comorbidities, which can complicate diagnosis and treatment. These factors can contribute to imbalanced medical data, making CSL an attractive approach to address these challenges and improve cancer care.

Cardiology and neurology received significant focus in subsequent order, constituting 15% (26 papers) and 12.7% (22 papers) of the investigated literature, respectively. CSL has demonstrated significant benefits in addressing cardiovascular and neurological diseases, widely recognized as significant health concerns. This finding is in line with the WHO's report ("Cardiovascular Diseases (CVDs)," 2021), which identifies cardiovascular diseases as the primary cause of mortality globally, responsible for 17.9 million deaths in 2019. Additionally, the WHO acknowledges that neurological disorders such as stroke, Alzheimer's disease, and other dementias are among the leading causes of disability and death worldwide ("Mental Health: Neurological Disorders," 2016.). Given the high mortality rate associated with these diseases, accurate predictions are imperative. However, data imbalance can lead to biased models that fail to capture important patterns in the data. By adopting CSL, researchers aim to improve prediction accuracy and contribute to preserving human life.

Infectious diseases occupied the fourth position, representing 8.7% (15 papers) of the total studies. Notable attention has been dedicated to researching this sub-field since 2020. This trend is not surprising, considering the urgency and global impact of the COVID-19 pandemic, which first emerged in 2019 and has since garnered substantial research attention.

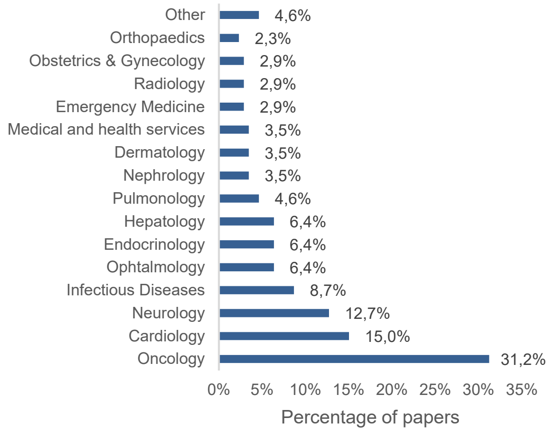

Figure 3: Distribution of the selected papers per medical discipline.

Additionally, imbalanced data is a common issue in COVID-19 studies due to various factors such as differences in testing availability and criteria, variations in reporting standards, differences in demographics, healthcare infrastructure, and compliance with public health measures. Besides, there may be a publication bias towards COVID-19 studies due to the pandemic's global impact, and funding agencies may have prioritized research on this topic. Lastly, data availability may have contributed to the popularity of COVID-19 as a research subject matter.

Other medical sub-fields, such as ophthalmology, endocrinology, and hepatology, were investigated by 11 papers (6.8%) each, demonstrating the relevance of cost-sensitive methods in these domains. Galdran and colleagues (Galdran, Dolz, Chakor, Lombaert, & Ben Ayed, 2020) highlighted the value of cost-sensitive classifiers in addressing two critical challenges in diabetic retinopathy grading. These classifiers can effectively model the complex structure of a heterogeneous label space and are also advantageous in addressing severely class-imbalanced scenarios. Fan et al. (Fan, Xie, Cheng, & Li, 2022) pointed out the inadequacy of conventional models in considering the imbalanced distribution of diabetic datasets and the varying misclassification costs across distinct patient categories. In a previous study by Yang et al. (2021), the predictive accuracy of traditional ML methods and cost-sensitive models were compared for predicting hepatic encephalopathy in cirrhotic patients. The study's results demonstrated the superiority of cost-sensitive models, underscoring their high suitability and potential for future prognosis studies.

Pulmonology was featured in 8 articles (4.6%), and nephrology, dermatology, and medical and health services were each investigated by six studies (3.5%). On the other hand, emergency medicine (2.9%), radiology (2.9%), and obstetrics & gynecology (2.9%) received relatively little attention, as did orthopaedics, which was addressed by only 2.3% of the selected studies (four papers).

Disciplines that received the least amount of attention in the selected studies were classified as "other", which included geriatric psychiatry and neonatology, each addressed by two papers (1.2%), as well as intensive care, radiomics, urology, and podiatry, which were each the focus of only one study (0.6%). This may be explained by factors such as limited data availability and researchers prioritizing other research areas deemed more crucial and pertinent to patient care.

3.4 MQ3: Which CSL Approaches Were Most Frequently Used in Medicine?

This study seeks to categorize the selected papers according to the CSL approaches they have employed, with the goal of obtaining a thorough understanding of the distribution and prevalence of these approaches within the medical literature.

Figure 4 illustrates the distribution of cost-sensitive approaches used in the selected studies. Direct approaches account for the largest share of papers, representing 76% (133 papers) of the qualified studies. Some researchers modified the objective function of the model to minimize the expected cost of misclassification (e.g., (Al-Sawwa & Ludwig, 2019)), while others incorporated the cost matrix directly into the loss function (e.g., (Ben naceur, Akil, Saouli, & Kachouri, 2020)). The ease of implementation is the primary factor contributing to this trend since most ML libraries offer readily available implementations (Sterner et al., 2021).

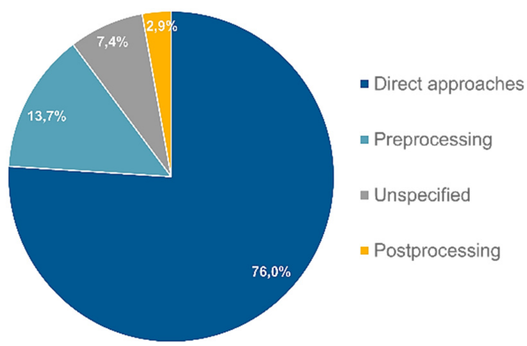

Figure 4: Distribution of the selected studies per CSL approach.

Moreover, certain packages offer the flexibility to apply custom loss functions directly to the algorithm, allowing users to employ cost-sensitive loss functions tailored to their specific applications.

A considerable share of the selected studies (16.6%) adopted meta-learning approaches. Precisely, preprocessing was applied in 24 papers (13.7%), and postprocessing was employed in 5 papers (2.9%). Preprocessing was carried out using weighting (e.g. (K. J. Wang, Makond, & Wang, 2013)) or MetaCost (e.g., (Afzal et al., 2013)), while postprocessing relied on thresholding (e.g., (Zhao, Wong, & Tsui, 2018)). Preprocessing techniques are adopted by researchers as they alter the training data instead of the underlying algorithm (Fernández et al., 2018), rendering them a suitable approach for different types of classifiers. Thresholding is less frequently employed in the selected studies due to the arduous task of selecting the most suitable threshold from a large pool of possibilities (Liu et al., 2021).

Note that the direct and preprocessing approaches were utilized together in two papers, resulting in double counting in these categories. Moreover, 13 articles (7.4%) did not provide information on the cost-sensitive approach they adopted and were thus categorized as "unspecified". Incomplete reporting may hinder the reproducibility and comparability of results and the identification of effective methods for dealing with imbalanced medical data. Given the importance of transparency in medical research, future studies should provide a clear and detailed description of the implemented cost-sensitive techniques, including any modifications made to the model, to allow for better understanding, comparison and replication of findings.

4 CONCLUSION AND FUTURE WORK

This SMS aimed to provide a thorough overview of the current state of research on CSL for imbalanced medical data. 173 papers published between January 2010 and December 2022 were selected from five digital libraries and classified according to publication years, channels and sources, medical disciplines, and CSL approaches. The main findings per MQ are: (MQ1) The use of CSL for imbalanced medical data has garnered increasing interest, particularly since 2020, with most papers (69.9%) published in journals. (MQ2) Oncology was the most extensively investigated discipline. (MQ3) Most papers (76%) employed CSL direct approaches. This SMS lays the groundwork for our forthcoming research, which will involve a more targeted and comprehensive review of CSL for imbalanced medical data.

ACKNOWLEDGEMENTS

This work was conducted under the research project "Machine Learning based Breast Cancer Diagnosis and Treatment", 2020-2023. The authors would like to thank the Moroccan Ministry of Higher Education and Scientific Research, Digital Development Agency (ADD), and CNRST for their support.

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