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Anomaly Detection in Medical Images Using SMOTE Algorithm: A Comprehensive Approach

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Abstract— *Anomaly detection in medical imaging is pivotal for early diagnosis and treatment planning. However, the inherent class imbalance in medical datasets poses significant challenges, often leading to biased models that underperform on minority classes. This study investigates the integration of the Synthetic Minority Over-sampling Technique (SMOTE) with various machine learning and deep learning models to enhance anomaly detection in medical images. By applying SMOTE to balance datasets and evaluating its impact across multiple models, we demonstrate improved detection accuracy, sensitivity, and specificity. The findings underscore the efficacy of SMOTE in addressing class imbalance, thereby enhancing the reliability of anomaly detection systems in medical imaging.*

Keywords— ***Anomaly Detection, Medical Imaging, SMOTE, Class Imbalance, Machine Learning, Deep Learning***

I. INTRODUCTION

In recent years, medical imaging has emerged as an indispensable tool in healthcare, aiding in the early diagnosis, treatment planning, and continuous monitoring of a wide range of diseases. Modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), X-ray, Ultrasound, and retinal fundus photography provide detailed, non-invasive visualization of the human body, allowing clinicians to detect subtle abnormalities that may indicate serious conditions. With the increasing digitization of healthcare systems and the growing availability of medical image datasets, automated anomaly detection has become a vital area of research, aiming to support radiologists and clinicians in decision-making and reduce diagnostic errors.

Anomaly detection in medical images refers to the process of identifying unusual patterns, structures, or regions that deviate from the norm, potentially indicating the presence of disease. However, this task presents several challenges. One of the most significant is class imbalance — a scenario where the number of normal cases far exceeds the number of abnormal (anomalous) ones. This imbalance leads to biased learning in supervised models, where classifiers tend to favor the majority class (normal), thereby failing to correctly identify minority class instances (anomalies). In the medical domain, such failures are critical, as they may lead to missed diagnoses and delayed treatments.

To mitigate the effects of class imbalance, various resampling techniques have been proposed. One of the most widely used and effective methods is the Synthetic Minority Over-sampling Technique (SMOTE). SMOTE generates synthetic examples of the minority class by interpolating between existing instances, thereby balancing the class distribution without simply duplicating samples. This helps in presenting the learning algorithm with a more representative view of both classes, enhancing its ability to detect anomalies in medical images. The utility of SMOTE has been demonstrated across several domains; however, its systematic application and evaluation within medical image analysis — particularly in deep learning contexts — remains an evolving area.

Moreover, modern machine learning and deep learning models such as Support Vector Machines (SVM), Random Forests, Convolutional Neural Networks (CNNs), and transformer-based architectures have shown significant promise in medical image classification and anomaly detection. Yet, these models are data-hungry and highly sensitive to data distribution. When trained on imbalanced datasets, they tend to overfit to the dominant class. This is where SMOTE plays a crucial role — by enriching the dataset with balanced, synthetic samples, it allows models to learn more generalizable features of both normal and abnormal cases.

In this research, we focus on the integration of SMOTE with various machine learning and deep learning models to improve anomaly detection performance in medical imaging tasks. We evaluate the effect of SMOTE on datasets such as brain MRI scans and retinal images, assessing improvements in key performance metrics like accuracy, sensitivity, specificity, and F1-score. Through extensive experimentation and comparative analysis, we demonstrate that incorporating SMOTE significantly enhances model robustness and diagnostic reliability.

This paper is structured as follows: Section 2 provides a detailed review of related work in anomaly detection and SMOTE applications. Section 3 outlines the methodology, including dataset description, preprocessing steps, model architectures, and evaluation metrics. Section 4 presents the proposed framework and comparative analysis with and without SMOTE. Section 5 discusses potential future work, and Section 6 concludes the paper with references.

II. LITERATURE REVIEW

The domain of anomaly detection in medical images has gained significant attention due to its critical role in clinical diagnostics. Accurate detection of abnormalities in modalities such as MRI, CT scans, and X-rays is vital for early disease detection and treatment planning. However, the high-dimensional nature of medical images and the inherent class imbalance — where normal cases vastly outnumber pathological ones — pose significant challenges for traditional machine learning models. Various approaches have been developed to address these issues, ranging from classical statistical methods to advanced deep learning models.

One of the earliest and most common techniques for anomaly detection in medical imaging involved **autoencoders**, which are unsupervised learning models trained to reconstruct input data. When trained exclusively on normal samples, autoencoders can effectively highlight anomalies by measuring reconstruction error. Shvetsova et al. (2021) proposed a deep perceptual autoencoder that leverages perceptual loss rather than traditional pixel-wise loss, improving the sensitivity of anomaly detection in chest X-rays and MRIs. While autoencoders are effective, their performance is limited in highly complex datasets and when class imbalance significantly skews training representations.

Generative Adversarial Networks (GANs) have also been widely adopted for anomaly detection. GANs can model the distribution of normal medical images and detect anomalies by identifying deviations from this distribution. Studies such as those by Ounasser et al. (2024) showed that GANs could be used to generate realistic-looking medical images that improve the performance of anomaly detectors. Nevertheless, training GANs is computationally expensive and sensitive to hyperparameter tuning, which can limit their usability in real-world medical settings.

Another popular strategy is **transfer learning**, where models pre-trained on large datasets such as ImageNet are fine-tuned on medical image data. This approach has shown significant promise due to the scarcity of labeled medical data. Alam et al. (2024) demonstrated that using SMOTE in conjunction with transfer learning models, such as ResNet and EfficientNet, resulted in significant performance gains in detecting diabetic retinopathy from retinal images. Transfer learning thus offers a practical pathway for leveraging powerful deep learning models while addressing data limitations.

The **Synthetic Minority Over-sampling Technique (SMOTE)** is a widely recognized method to handle class imbalance in machine learning. Initially proposed by Chawla et al., SMOTE creates synthetic examples of the minority class by interpolating between existing minority class samples. In medical imaging, SMOTE has been applied to a variety of datasets, improving the performance of classifiers such as Random Forests, Support Vector Machines, and CNNs. For example, Hasan et al. (2023) integrated SMOTE with Edited Nearest Neighbour and Mixup to create a robust pipeline for medical anomaly detection, demonstrating marked improvements in classification metrics like recall and F1-score.

Several studies have explored **hybrid techniques** that combine SMOTE with other sampling strategies and advanced neural networks. For instance, Siddalingappa (2022) combined SMOTE with CNNs to detect COVID-19 from chest X-rays. The use of SMOTE not only improved classification accuracy but also ensured the minority

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class (i.e., infected cases) was sufficiently represented, reducing false negatives. Similarly, hybrid techniques like SMOTE-ENN (Edited Nearest Neighbor) and Borderline-SMOTE have been found to outperform standard SMOTE in datasets where noise is a concern.

More recent approaches have begun leveraging **transformer architectures** and attention mechanisms in medical image analysis. Rashmi et al. (2024) introduced the Ano-swinMAE model, which used a Swin Transformer-based masked autoencoder for anomaly detection in brain MRI scans. While these models show state-of-the-art performance, they too are affected by class imbalance issues, which can be alleviated by data augmentation and resampling strategies like SMOTE.

Despite these advancements, challenges remain. Many anomaly detection systems still struggle with interpretability, a key concern in clinical practice. Moreover, existing models often lack robustness to domain shifts, such as variations in imaging equipment or protocols. Tschuchnig and Gadermayr (2021) emphasized that while unsupervised and semi-supervised methods hold promise, they must be rigorously evaluated on diverse datasets to ensure generalizability.

In conclusion, the literature illustrates a clear trend toward integrating data balancing techniques like SMOTE with deep learning architectures for improved anomaly detection in medical imaging. Although SMOTE has proven beneficial in enhancing classifier performance, especially on minority classes, its effectiveness varies based on the dataset and model architecture. Future research must continue to refine these techniques, explore novel variants of SMOTE, and develop explainable AI systems that can gain acceptance in clinical settings.

III. METHODOLOGY

3.1 Dataset

The study utilizes publicly available medical imaging datasets, including:

- **Brain Tumor MRI Dataset:** Comprising T1-weighted contrast-enhanced images labeled as normal or tumor.
- **APTOS 2019 Blindness Detection Dataset:** Containing retinal images labeled for diabetic retinopathy severity.

3.2 Data Preprocessing

Images are resized to a uniform dimension, normalized, and augmented using techniques such as rotation, flipping, and scaling to enhance model generalization.

3.3 SMOTE Application

SMOTE is applied to the training datasets to synthetically generate minority class examples, thus balancing the class distribution.

3.4 Model Training

Various models are trained on the balanced datasets, including:

- **Convolutional Neural Networks (CNNs):** For feature extraction and classification.
- **Support Vector Machines (SVMs):** For classification tasks.
- **Random Forests:** For ensemble learning and classification.

Hyper parameters are tuned using cross-validation to optimize model performance.

IV. PROPOSED WORK AND COMPARATIVE ANALYSIS

The proposed framework integrates SMOTE with CNNs for anomaly detection in medical images. The performance of models trained on original and SMOTE-balanced datasets is compared using metrics such as accuracy, sensitivity, specificity, and F1-score.

Table 1: Performance Comparison

Model	Dataset	Accuracy	Sensitivity	Specificity	F1-Score
CNN (Original)	Brain Tumor MRI	85.2%	80.5%	89.9%	82.3%
CNN (SMOTE)	Brain Tumor MRI	91.4%	89.7%	93.1%	90.5%
SVM (Original)	APTOS 2019	78.6%	75.0%	82.2%	76.8%
SVM (SMOTE)	APTOS 2019	84.3%	81.5%	87.1%	82.9%

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Fig.1: Accuracy Comparison Graph

The results indicate that applying SMOTE significantly improves model performance across various metrics, highlighting its effectiveness in addressing class imbalance in medical imaging datasets.

V. FUTURE WORK

Future research directions include:

- **Integration with Advanced Models:** Combining SMOTE with advanced architectures like transformers for enhanced performance.
- **Real-Time Implementation:** Developing real-time anomaly detection systems for clinical settings.
- **Multi-Modal Data:** Extending the framework to handle multi-modal medical data for comprehensive analysis.
- **Explainability:** Incorporating explainable AI techniques to provide insights into model decisions, aiding clinical interpretability.

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