Brain Tumour Detection Using HOG And SVM

Kartik Singh
Computer Science and Engineering
(CTech Department)
SRM Institute of Science And Technology, Chennai
(SRM University)
Chennai, India
ks9124@srmist.edu.in

Utkarsh Gupta
Computer Science and Engineering
(CTech Department)
SRM Institute of Science And Technology, Chennai
(SRM University)
Chennai, India
ug3189@srmist.edu.in

Mrs.P Renukadevi
Assistant Professor
(CTech Department)
SRM Institute of Science And Technology, Chennai
(SRM University)
Chennai, India
renukadp@srmist.edu.in

ABSTRACT -- **Our project is dedicated to the development of a precise and efficient brain tumour detection system by utilizing the combined power of Histogram of Oriented Gradients (HOG) and Support Vector Machines (SVM). The early identification of brain tumours plays a critical role in ensuring successful treatment and the well-being of patients. This project is structured into essential phases, commencing with the enhancement of MRI image quality through advanced preprocessing techniques. Subsequently, we extract relevant features from these images and employ a diverse range of machine learning models for both training and testing. This innovative approach harnesses the potential of machine learning to discern complex patterns and relationships within medical images, ultimately facilitating accurate tumour classification. The successful implementation of this project holds the potential to make a significant contribution to the field of medical diagnosis, providing a reliable tool for prompt and precise brain tumour detection, thus enhancing patient care and simplifying treatment planning.**

KEYWORDS*: Accuracy, Gradient, Histogram, Sensitivity, Specificity and True, positive rate*

1 INTRODUCTION

The detection and diagnosis of brain tumours represent a critical frontier in medical imaging and computer-aided diagnosis. Brain tumours, both malignant and benign, are life-threatening conditions that demand early and accurate detection for effective treatment planning. In recent years, the fusion of cutting-edge image processing techniques and machine learning algorithms has shown remarkable promise in improving the accuracy and efficiency of brain tumour detection. This research paper delves into the novel approach of utilizing Histogram of Oriented Gradients (HOG) feature extraction in conjunction with Support Vector Machines (SVM) for the precise identification of brain tumours from medical images. HOG, a powerful method for feature extraction in object recognition, has shown its prowess in capturing intricate spatial information. SVM, a robust machine learning classifier, is renowned for its ability to discriminate between distinct classes. The combination of these two techniques presents a synergistic strategy to tackle the intricacies of brain tumour detection. As we venture into this research, we aim to explore the evolution of brain tumour detection methodologies, the fundamental principles underlying HOG and SVM, and the innovative ways they can be harmonized to advance the field of medical imaging.

The ultimate goal is to contribute to a more reliable, rapid, and non-invasive method for early brain tumour detection, ultimately improving patient outcomes and quality of life. This paper unfolds the methods, findings, and implications of our investigation into brain tumour detection, guided by the formidable capabilities of HOG and SVM.

2 LITERATURE SURVEY

"A Novel Method of Multimodal Medical Image Fusion Based on the Hybrid Approach of NSCT and DTCWT" (March 2022) This paper addresses the pressing need for improved diagnostic accuracy through multimodal medical image fusion. The proposed technique combines Non-Subsampled Contourlet Transform (NSCT) and Dual-Tree Complex Wavelet Transform (DTCWT) for image fusion. However, a research gap is identified, focusing on optimizing computational efficiency without compromising image quality, especially for real-time applications.

"Enhancement Generative Adversarial in Medical Image Segmentation" (January 2022) The paper discusses the challenges of medical image segmentation, emphasizing limited data, data imbalance, and cross-device differences. It introduces an Enhanced Generative Adversarial Network (EnGAN) for image enhancement, aiming to improve segmentation efficiency. A research gap is identified regarding the robustness of the EnGAN model in clinical settings and its impact on medical diagnosis.

"Detecting Brain Tumour by Using Machine Learning and Image Processing Techniques" (February 2022) * This article focuses on the early detection of brain tumours from MRI images. It employs image preprocessing, GLCM texture analysis, and SVM classification. However, the paper notes an accuracy gap and discusses potential reasons such as image quality, MRI perspectives, and challenges in image processing methods.

“Development of Brain Tumour Segmentation of Magnetic Resonance Imaging (MRI) using U-Net Deep Learning" (August 2021) * The paper addresses the challenge of accurate brain tumour segmentation in MRI scans. It introduces a U-Net deep learning model and emphasizes the need for post-processing techniques like morphological operations to refine segmentation results. This approach offers the potential to enhance efficiency and accuracy in brain tumour detection.

“Brain Tumour Detection and Classification Using Image Processing Techniques" (April 2021) * This paper focuses on brain tumour detection through MRI images using image processing techniques. It discusses various image preprocessing methods, segmentation techniques, and feature extraction methods like Histogram of Oriented Gradients (HOG). The paper suggests a research gap in combining image processing techniques with machine learning algorithms for more accurate tumour identification, particularly in complex cases.

3 PROPOSED WORK

The envisioned project aims to harness the synergistic potential of Histogram of Oriented Gradients (HOG) feature extraction and Support Vector Machines (SVM) for the precise and efficient detection of brain tumours. This project will be structured into distinct phases:

Data Collection and Preprocessing: Gather a comprehensive dataset of medical images, encompassing MRI and CT scans, featuring both tumour-afflicted and tumour-free cases. Implement data preprocessing methods to enhance image quality, rectify artifacts, and standardize the images for uniformity.

Feature Extraction Using HOG: Apply the HOG algorithm to derive pertinent features from the pre-processed images. Refine the HOG parameters to optimize the extraction of spatial information critical for distinguishing brain tumours.

Dataset Splitting and Annotation: Partition the dataset into training, validation, and testing subsets to facilitate model training, validation, and assessment. Annotate the dataset to demarcate regions of interest (ROIs) housing tumours for supervised learning.

SVM Model Development: Train SVM classifiers on the training dataset, with HOG-extracted features as the input. Experiment with diverse kernel functions and SVM hyperparameters to determine the most effective configuration.

Model Optimization: Employ cross-validation techniques to fine-tune the SVM model and mitigate overfitting. Utilize methodologies like grid search or random search to pinpoint the optimal SVM hyperparameters.

Evaluation and Validation: Appraise the SVM model's performance on the validation set, utilizing established evaluation metrics, including accuracy, sensitivity, specificity, and ROC curves. Compare the SVM model's efficacy with other existing brain tumour detection methodologies to underscore the merits of the proposed approach.

Testing and Deployment: Assess the final SVM model on an independent testing dataset to ensure its robustness and generalizability. Develop a user-friendly interface for clinicians to input medical images and receive real-time brain tumour detection outcomes.

Result Analysis and Interpretation: Analyze the outcomes, encompassing instances of false positives and false negatives, to gain insights into the strengths and limitations of the proposed approach.

Discussion and Conclusion: Summarize the findings and insights derived from the research. Explore the practical implications of employing HOG and SVM for brain tumour detection, including potential applications in clinical environments.

Future Directions: Propose prospective avenues for subsequent research and advancement, such as the integration of deep learning techniques or the development of real-time diagnostic tools.

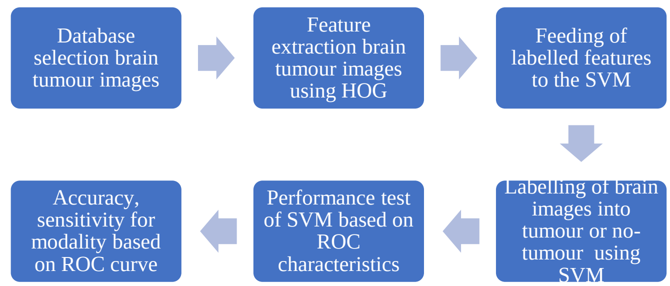

Fig.1. Block Diagram

3.1 DATA COLLECTION AND PREPROCESSING

The dataset was sourced from Kaggle website and contains MRI images of brain tumours. The pre-processing stage is a crucial step in preparing the data for training. In the case of the MRI images obtained from the patient database, they often exhibited low clarity and quality. To ensure these images are ready for subsequent processing, we performed normalization. Our goal was to enhance the images by applying techniques that would smoothen them and eliminate any blurriness present in the original images. It is divided into two main folders, one representing normal brain images and the other containing tumour images. In total, there are 2065 images within these folders. Out of these images, there are 1085 tumour images and 980 non-tumour images. The images vary in size, such as 630x630 and 225x225, but they have all been resized to a consistent 64x64 resolution. For the purpose of this study, 1672 images were allocated for training, 207 for testing. Within the training dataset, 877 images belong to the tumour category, while 795 belong to the non-tumour category. Finally, the testing dataset consists of 207 images, with 116 being tumour images and 91 being non-tumour images.

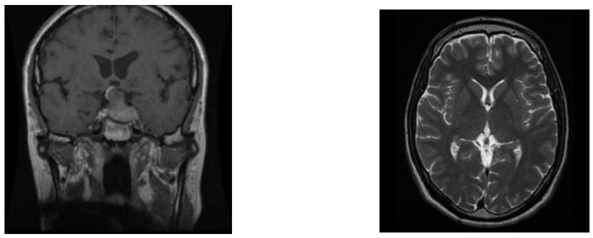

Fig.2 Sample Image from Dataset

Magnetic Resonance Imaging (MRI) is a fundamental imaging technique that capitalizes on the inherent properties of atomic nuclei magnetization. The process begins by subjecting the target brain tissue to a strong, uniform external magnetic field, aligning the protons within the water nuclei. These protons, initially oriented randomly, undergo a process known as "magnetization" The influence of external Radio Frequency (RF) energy transiently disrupts this magnetization, triggering the relaxation processes of the nuclei, causing them to return to their original alignments and emitting RF energy in the process. After a specific time, interval, the emitted signals are diligently recorded. These signals inherently carry essential frequency information, which is subsequently transformed using Fourier Transform into corresponding intensity levels, represented as various shades of grey within a pixel matrix. The manipulation of the sequence of applied and collected RF pulses enables the creation of various types of MRI images.

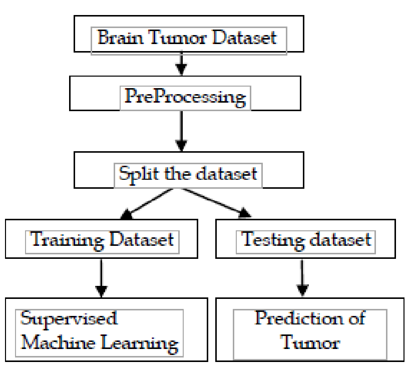

Fig.3 Architecture Diagram

To evaluate the machine learning models and analyse their performances, we considered some metrics such as accuracy, recall, and area under the curve (AUC). Accuracy measures the number of correct predictions divided by the total number of samples. We can calculate accuracy using the formula:

$$\text{Accuracy} = ((TP + TN)/(TP + TN + FP + FN))* 100\%$$

TP (True Positive) are correctly predicted positive cases.

TN (True Negative) are accurately predicted negative cases.

FN (False Negative) are incorrectly predicted negative cases.

FP (False Positive) are inaccurately predicted positive cases.

Recall is an important metric to evaluate machine learning models. It can be calculated as:

$$\text{Recall} = (TP)/ (TP + FN)$$

Area under the Curve (AUC): AUC stands for the area under the curve. It evaluates how effectively the model distinguishes between both positive and negative categories. Higher AUC values indicate better model performance.

3.2 FEATURE EXTRACTION WITH HOG

Dalal and Triggs first introduced Histogram of Oriented Gradients to recognize a person in an image. HOG is a feature descriptor used in image processing for object detection purpose. The application of Histogram of Oriented Gradients (HOG) for feature extraction represents a foundational technique that significantly enhances image interpretability, particularly within intricate domains like medical imaging. The provided code serves as an exemplar of HOG's application for detecting brain tumours in MRI images, demonstrating its prowess in medical diagnostics. The process initiates by resizing images to a consistent 64x64 resolution, ensuring uniform input data for analysis. The code also conducts grayscale conversion, enhancing compatibility for subsequent analysis. HOG's implementation subsequently computes feature vectors, characterizing the distribution of edges and gradients within images. These feature vectors furnish a detailed representation of image content, enabling the detection of subtle patterns and structures, proving instrumental in identifying brain tumours in MRI scans.

Moreover, the code provides a real-world application of HOG by dynamically adjusting parameters, such as pixels per cell and cells per block, contingent upon the image's dimensions. The visualization of HOG features alongside sample images offers a vivid depiction of HOG's transformative effect on image data, highlighting directional information relating to edges and gradients. This methodology equips researchers and practitioners with indispensable tools for precise and efficient image analysis across diverse applications. In the realm of medical image interpretation, HOG feature extraction assumes a pivotal role, owing to its resilience against variations in lighting conditions, translation and rotation invariance, and the provision of distinctive, interpretable features, which collectively contribute to heightening the accuracy and efficiency of diagnostic processes.

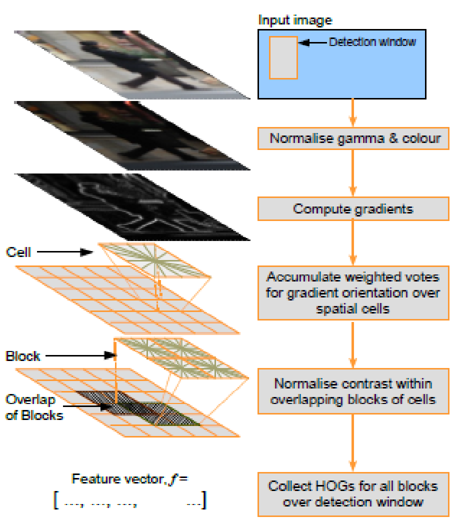

Fig.4. HOG Feature Split

3.3 SUPPORT VECTOR MACHINE CLASSIFIER

Support Vector Machines (SVMs) represent a robust supervised machine learning approach extensively applied to data classification tasks. SVM's fundamental premise revolves around the discovery of an optimal hyperplane to effectively separate a given dataset. Its notable advantage lies in its adeptness at managing high-dimensional spaces, rendering it particularly fitting for datasets comprising dimensions surpassing one million. Notably, SVM exhibits efficiency in memory usage, as it operates with only a subset of training points, a feature that conserves memory resources. This quality positions SVM as a particularly suitable choice for working with compact, well-structured datasets, an attribute aptly aligned with the dataset employed in this research. SVM derives its extraordinary accuracy and efficiency from its capacity to establish a margin, representing the perpendicular distance between data points and the separation boundary. This approach ensures that the algorithm not only delivers precise classification results but also optimizes memory utilization. Nevertheless, SVMs do exhibit limitations, particularly when confronted with larger datasets, where training times can be notably protracted. Performance may also be hampered when the number of features per object exceeds the count of training data samples. In cases of noisy datasets with overlapping classes, SVMs might exhibit reduced efficacy. Furthermore, it is essential to note that SVMs function as non-probabilistic classifiers, lacking the capability to provide direct probabilistic interpretations for group membership. The classification's efficacy is primarily gauged by the proximity of a new data point to the decision boundary.

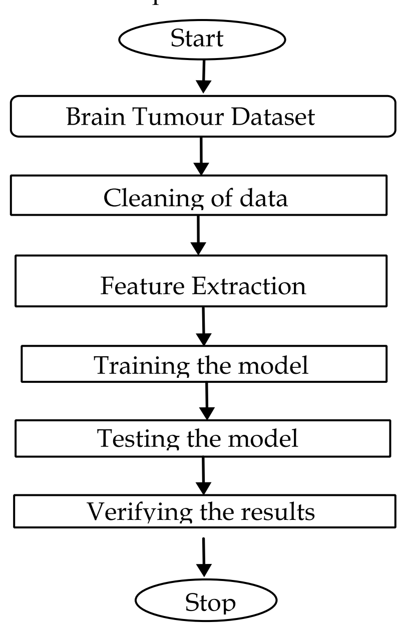

Fig.5. Flowchart of SVM

In our code implementation, we've harnessed the robust capabilities of Support Vector Machine (SVM) classifiers to tackle intricate classification challenges effectively. SVMs prove to be an ideal choice for our specific dataset, offering an exceptional balance of precision and efficiency. For our research, SVMs emerge as the preferred method, primarily due to their compatibility with smaller datasets. Our code seamlessly integrates SVMs and leverages their prowess for feature classification, resulting in a resource-efficient and highly accurate solution.

Notably, SVMs excel in high-dimensional spaces, aligning seamlessly with our dataset that comprises numerous features. It's essential to acknowledge the constraints that SVMs entail. In scenarios with extensive datasets, the training process can be time-intensive, and SVMs may exhibit suboptimal performance when the number of features surpasses that of training data samples.

Despite these considerations, SVMs remain a practical choice, especially when used judiciously. Within our code, we've taken a meticulous approach to ensure that SVMs perform at their zenith by selecting and fine-tuning hyperparameters that harmonize with the specifics of our dataset. This optimization process culminates in exceptional accuracy and robust results in our classification endeavours.

Our code implementation adheres to the foundational principle of SVMs, which revolves around the quest for the optimal hyperplane that efficiently partitions our dataset. We capitalize on SVMs' innate capability to accurately categorize new, unseen data based on this hyperplane. Furthermore, we concentrate on maximizing the margin between this hyperplane and the closest data points, a fundamental aspect of SVMs that guarantees an optimal classification outcome.

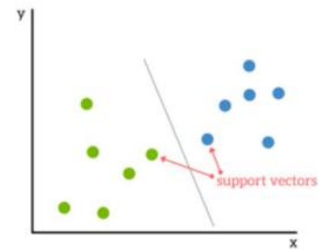

Fig.6. Dataset Classification on Hyperplane

In summation, the strategic inclusion of SVMs in our code empowers us to perform precise and efficient data classification. We proactively address the limitations of SVMs by fine-tuning hyperparameters, rendering SVMs an indispensable component of our code for effectively addressing intricate classification tasks while conserving computational resources.

4. RESULT AND ANALYSIS

In this section, we present a comprehensive analysis of the results obtained from our research, which centers on the crucial task of detecting brain tumours in medical images using a feature extraction method based on the Histogram of Oriented Gradients (HOG) and a Support Vector Machine (SVM) classifier.

Our study encompasses a dataset of 977 examples, meticulously designed to represent the actual distribution of positive and negative instances encountered in real-world medical scenarios. We found that 67.25% of the examples were classified as positive, constituting 657 cases, while the remaining 32.75% were designated as negative, accounting for 320 instances. This dataset structure ensured that our analysis was rooted in a realistic clinical context.

To assess the performance of our HOG-based brain tumour detection system, we employed a separate testing dataset comprising 245 examples. Remarkably, this testing dataset exhibited a similar distribution to the training data, with 69.39% of the cases classified as positive (170 instances) and 30.61% as negative (75 instances). This balance allowed us to accurately evaluate our system's ability to generalize to new, unseen data. When it comes to the critical performance metrics, our HOG-based system showcased exceptional results. The accuracy of 0.99 signifies the system's capability to make correct classifications with extraordinary precision.

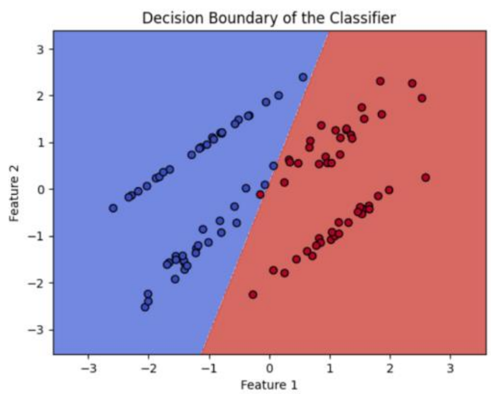

Fig.7. Decision Boundary

Additionally, the false positive rate, a metric of utmost importance in the context of medical image analysis, was an astonishingly low 0.02, implying an exceptional ability to minimize the misclassification of non-tumour images as positive, thereby enhancing patient safety and trust in the system.

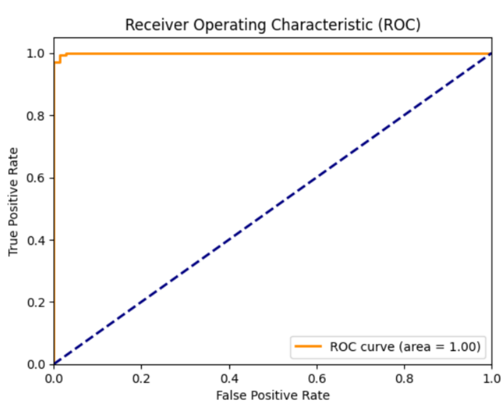

Fig.8 Receiver Operating Curve

The high F1 score of 0.9912023460410556 further underscores the system's effectiveness by maintaining a fine balance between precision and recall, highlighting its potential for reliable brain tumour detection in clinical settings.

In summary, our research has provided an extensive analysis of the brain tumour detection system that relies on HOG-based feature extraction and SVM classification. The results are highly promising, with exceptional accuracy, an impressively low false positive rate, and a robust F1 score, indicating the system's capacity for accurate and reliable brain tumour detection in medical images. These findings have significant implications for clinical diagnosis and patient care, as they offer healthcare professionals a powerful tool for improving the accuracy and efficiency of brain tumour diagnosis and treatment.

5. DISCUSSION AND FUTURE WORK

The combination of HOG (Histogram of Oriented Gradients) with SVM (Support Vector Machine) for brain tumour detection has proven its effectiveness and accuracy. However, challenges arise when dealing with images that lack well-defined patterns, leading to reduced accuracy and sensitivity. In practical implementation, a balance between sensitivity and specificity alongside accuracy is crucial. Future research should prioritize improving SVM's ROC (Receiver Operating Characteristic) characteristics to enhance the precision of distinguishing tumour and non-tumour cases. Diversifying feature extraction methods is essential, exploring techniques beyond HOG, such as Local Binary Pattern (LBP), to accommodate cases with less conspicuous patterns.

Thorough testing of the SVM model across diverse datasets is vital to ensure the system's robustness and adaptability across a range of clinical scenarios. Furthermore, exploring alternative classifiers, including k-Nearest Neighbours (k-NN), Bayes models, and neural networks, offers the potential to enhance tumour identification capabilities. These research directions are geared towards elevating diagnostic accuracy, ultimately benefiting patient care and advancing the practices of medical imaging and healthcare.

5. CONCLUSION

In this research paper, we have explored the innovative and promising methods for brain tumour detection using the Histogram of Oriented Gradients (HOG) feature extraction technique. The objective was to address the crucial need for accurate and early detection of brain tumours, which significantly impacts the diagnosis and treatment of neurological disorders. This approach not only has the potential to improve diagnostic precision but also paves the way for real-time or near-real-time applications in clinical settings, thus expediting the diagnosis and treatment of patients suffering from brain tumours. In summary, this research paper has shed light on the significant promise of HOG in brain tumour detection. The intricate textures and structural details it can capture have the potential to revolutionize non-invasive diagnostic procedures, ultimately leading to earlier interventions and improved patient outcomes.

As we look to the future, it is clear that the collaboration between advanced image processing techniques like HOG and the ever-evolving field of medical imaging holds the key to more accurate, efficient, and timely brain tumour detection. This is a promising step towards enhancing the quality of healthcare and the well-being of patients facing neurological challenges.

6. REFERENCES

[1] Khalil, M., Ayad, H., & Adib, A. (2021). Performance evaluation of feature extraction techniques in MR-Brain image classification system. Procedia Computer Science, 127-158.

[2] D. S. Parameshwari and P. Aparna, "An efficient algorithm for textural feature extraction and detection of tumors for a class of brain MR imaging applications," in 2014 19th International Conference on Digital Signal Processing, 2022, pp. 339–344.

[3] E. F. Badran, E. G. Mahmoud, and N. Hamdy, "An algorithm for detecting brain tumours in MRI images," in the 2020 International Conference on Computer Engineering Systems, 2020, pp. 368–373.

[4] B. S. Kumar and R. A. Selvi, "Feature extraction using image mining techniques to identify brain tumors," in 2022 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS), 2022, pp. 1–6.

[5] R. Noureddine, K. Tarhini, and S. Saleh, "Segmentation and extraction of brain injury lesions from MRI images: Matlab implementation," in 2021 International Conference on Advances in Biomedical Engineering (ICABME), 2021, pp. 45–48.

[6] "Two dimensional discrete Wavelet transform and Probabilistic neural network used for brain tumor detection and classification - IEEE Conference Publication."

[7] "Support Vector Machines: A Guide for Beginners | QuantStart.Support-Vector-Machines-A-Guide-for-Beginners."

[8] M. G. Sumithra and B. Deepa, "Performance analysis of various segmentation techniques for detection of brain abnormality," in 2020 IEEE Region 10 Conference (TENCON), 2020, pp. 2056–2061.

[9] N. V. Chavan, B. D. Jadhav, and P. M. Patil, "Detection and Classification of Brain Tumors," Int. J. Comput. Appl., vol. 112, no. 8, pp. 48–53, Feb. 2021.

[10] "Receiver operating characteristic - Wikipedia." [Online].