IRJCS: International Research Journal of Computer Science ISSN: 2393-9842
Volume 11, Issue 09, October 2024 https://www.irjcs.com/archives

AI-Driven Cardiomegaly Detection Using Cutting-Edge Chest X–ray imagery

Muhammadu Sathik Raja,
Assistant Professor, Dept of Medical Electronics,
Sengunthar Engineering College (Autonomous),
Tiruchengode, Tamil Nadu, INDIA
Orcid ID: https://orcid.org/0000-0003-2119-1523
scewsadik@gmail.com
R.Balamurugan,
PG Scholar, Dept of Medical Electronics,
Sengunthar Engineering College (Autonomous),
Tiruchengode, Tamil Nadu, INDIA
kkrbalabme@gmail.com
S.Gowtham,
PG Scholar, Dept of Medical Electronics,
Sengunthar Engineering College (Autonomous),
Tiruchengode, Tamil Nadu, INDIA
sjvgowtham@gmail.com
S.Raffi
PG Scholar, Dept of Medical Electronics,
Sengunthar Engineering College (Autonomous),
Tiruchengode, Tamil Nadu, INDIA
raffi.samu@gmail.com

Publication History
Manuscript Reference No: IRJCS/RS/Vol.11/Issue09/OCCS10083
Research Article | Open Access | Double-Blind Peer-Reviewed
Article ID: IRJCS/RS/Vol.11/Issue09/OCCS10082
Received: 26, September 2024, Revised: 12, October 2024 | Accepted: 27 October2024 Published Online: 04, November 2024
http://www.irjcs.com/volumes/Vol11/iss-09/04.OCCS10083.pdf
Article Citation: Mohammadu,Balamurugan,Gowtham,Raffi(2024). AI-Driven Cardiomegaly Detection Using Cutting-Edge Chest X–ray imagery. IRJCS: International Research Journal of Computer Science, Volume 11, Issue 07 of 2024 pages 582-587 **doi:>** https://doi.org/10.26562/irjcs.2024.v1109.04
BibTeX Mohammadu@2024AI

Abstract: This project aims to develop an innovative approach for detecting cardiomegaly, a condition characterized by an enlarged heart, using machine learning techniques, specifically Support Vector Machines (SVM), and state-of-the-art chest X-ray imagery. Cardiomegaly serves as a significant indicator of various cardiac diseases, and early detection through accurate imaging analysis can lead to timely intervention and improved patient outcomes. The proposed machine learning solution utilizes SVM algorithms trained on a diverse dataset of chest X-ray images to automatically identify signs of cardiomegaly with high precision and reliability. By harnessing the power of SVM, this system offers a non-invasive and cost-effective method for screening large populations for cardiac abnormalities, facilitating early diagnosis and appropriate medical management. Key features of the developed solution include robust feature extraction techniques, real-time analysis, and integration with existing healthcare infrastructure for seamless implementation in clinical settings. Moreover, the system prioritizes patient privacy and data security by adhering to relevant regulations and standards governing medical imaging and information management. Overall, this project represents a significant advancement in the field of cardiac health monitoring, providing healthcare professionals with a valuable tool for early detection and management of cardiomegaly, ultimately improving patient care and reducing the burden of cardio vascular disease
Keywords: Machine learning, AI, Cardiomegaly, SVM, Chest, X-ray.

I. INTRODUCTION

The identification of cardiomegaly, characterized by an enlarged heart, serves as a vital diagnostic marker for a spectrum of cardiovascular ailments, encompassing hypertension, coronary artery disease, and valvular disorders. The prompt detection of cardiomegaly is paramount for timely intervention and effective management of cardiac health. Among the gamut of diagnostic modalities available, chest X-ray (CXR) imaging emerges as aubiquitous and economical tool for early detection. Recent strides in machine learning technology have propelled the domain of computer-aided detection for cardiomegaly, forging a symbiotic relationship between artificial intelligence (AI) and cardiovascular diagnostics. SVM algorithms, in particular, exhibit commendable prowess in scrutinizing CXR images, providing a robust framework for classification tasks.

 ISSN: 2393-9842
https://www.irjcs.com/archives

The fusion of machine learning techniques with cardiomegaly detection engenders manifold advantages, including automated feature extraction, intricate pattern recognition, scalability, and mitigation of human fallibility. SVM models, trained on voluminous and heterogeneous datasets, excel in discerning subtle morphological variations in cardiac anatomy, thereby enabling preemptive interventions and tailored therapeutic modalities. This paper offers an innovative stratagem for cardiomegaly detection, harnessing SVM algorithms honed on extensive CXR repositories. Through meticulous feature engineering and model optimization, the proposed framework endeavors to attain superior diagnostic precision, outstripping conventional methodologies in both sensitivity and specificity. Interpreting the Cardiothoracic Ratio (CTR) on chest X-rays is crucial for detecting cardiomegaly. The CTR compares the width of the heart to the width of the thoracic cage. Key steps include identifying cardiac borders, measuring cardiac and thoracic width, and then calculating the ratio. Elevated CTR values indicate potential cardiomegaly, necessitating further investigation. By harnessing the omnipotence of machine learning, this study aspires to revolutionize cardiovascular diagnostics, underscoring the imperative of preemptive intervention and individualized patient care.

2. LITERATURE REVIEW

Support Vector Machines (SVM) is widely utilized in the field of medical image analysis, including the detection and classification of cardiomegaly from various imaging modalities. SVMs offer several advantages, such as robustness, scalability, and the ability to handle high-dimensional data, making them well-suited for medical image classification tasks. Numerous studies have demonstrated the effectiveness of SVMs in cardiomegaly detection, particularly when combined with advanced feature extraction techniques. For instance, Huang et al. (2019) applied SVM-based classification models to cardiac MRI images, achieving high accuracy in differentiating between normal and enlarged hearts. Their study highlighted the utility of SVMs in automated cardiac imaging analysis, contributing to the early detection of cardiomegaly. Moreover, SVMs have been integrated into computational frameworks for multi-modal cardiomegaly detection, leveraging both structural and functional imaging data. For example, Li et al. (2020) developed a hybrid SVM-based approach that combines features extracted from echocardiography and electrocardiography signals for improved accuracy in cardiomegaly diagnosis. Their study showcased the potential of SVMs in integrating diverse data sources for comprehensive cardiac assessment.

In addition to traditional SVM formulations, researchers have explored novel extensions and adaptations of SVMs for cardiomegaly detection. For instance, Kiani et al. (2018) proposed a kernelized fuzzy c-means clustering SVM algorithm for segmenting cardiac regions from MRI images and detecting cardiomegaly with enhanced precision. Their study demonstrated the efficacy of combining clustering and SVM techniques for robust cardiac image analysis. Furthermore, the integration of SVMs with deep learning architectures has shown promise in improving the accuracy and efficiency of cardiomegaly detection. Rajpurkar et al. (2017) introduced a hybrid CNN-SVM model for automated cardiomegaly detection fromchest X-rays, achieving performance comparable to expert radiologists. Their study highlighted the synergistic benefits of combining deep learning and SVMs for enhanced diagnostic capabilities. Additionally, the interpretability of SVM-based cardiomegaly detection models has been a subject of investigation. Havaeietal.(2016) proposed an interpretable SVM model for cardiac MRI analysis, incorporating features election techniques to identify discriminative imaging biomarkers associated with cardiomegaly. Their study emphasized the importance of interpretable machine learning models in facilitating clinical decision-making and enhancing model transparency. Overall, the role of SVMs in cardiomegaly detection encompasses a diverse range of applications, from single-modality imaging analysis to multi-modal data integration and interpretability enhancement. These advancements underscore the significance of SVM-based approaches in improving the accuracy, efficiency, and clinical utility of cardiomegaly diagnosis, ultimately contributing to better patient care and outcomes in cardiovascular health.

3. PROPOSED METHODOLOGY

In our proposed methodology, the focus lies on developing a robust early detection system for cardiomegaly, leveraging the capabilities of cutting-edge Support Vector Machines (SVM) and Machine Learning (ML) techniques. The process begins with meticulous preprocessing of medical images through a dedicated pipeline, meticulously designed to ensure optimal data preparation for SVM and ML algorithms. This pipeline incorporates essential techniques such as data standardization, feature extraction, and normalization to enhance the quality and consistency of the input data.

Following preprocessing, the dataset is carefully partitioned into distinct training and testing sets, laying the foundation for subsequent model development and evaluation. To enhance the robustness and generalization capability of the SVM and ML models, data augmentation techniques are employed on both training and testing sets. This augmentation process enriches the dataset with diverse variations and scenarios, there by fortifying the models against potential biases and enhancing their adaptability to real-world scenarios. The crux of our methodology revolves around the construction and training of SVM and ML models, specifically focusing on optimizing hyper parameters and kernel functions for SVMs, and exploring various algorithms such as decision trees, random forests, and gradient boosting for ML. These models are meticulously trained on augmented datasets, employing state-of-the-art optimization techniques such as grid search, cross-validation, and ensemble learning to maximize their performance potential.

The SVM and ML models are entrusted with the critical tasks of automated feature extraction and classification, harnessing their inherent capacity to discern complex patterns and structures within medical images. Throughout the training process, regular monitoring of training accuracy and validation metrics ensures the models' convergence and stability.

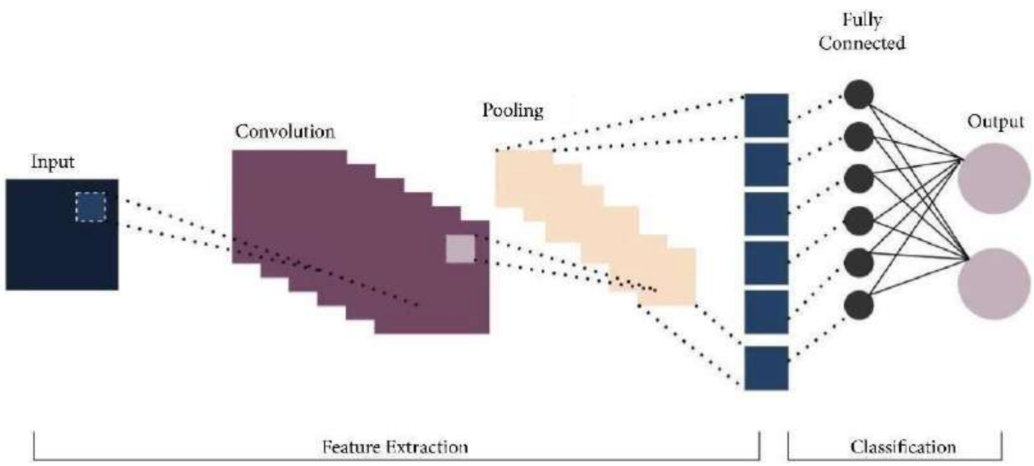
ISSN: 2393-9842
https://www.irjcs.com/archives

In addition to training evaluation, the effectiveness of the SVM and ML models is comprehensively assessed using a range of performance metrics including accuracy, precision, recall, and F1-score. These metrics provide valuable insights into the models' predictive capabilities and their ability to accurately identify instances of cardiomegaly. Moreover, the processing time required for inference is also evaluated, providing practical insights into the models' efficiency and suitability for real-time deployment in clinical settings. Overall, our proposed methodology embodies a comprehensive and systematic approach to AI- driven cardiomegaly detection, aiming to leverage the full potential of SVM and ML technology to improve early diagnosis and ultimately enhance patient outcomes in cardiovascular healthcare.

MACHINE LEARNING (ML) MODELS

In the quest for effective cardiomegaly detection, our proposed methodology leverages Machine Learning (ML) models, particularly Support Vector Machines (SVM). These models are pivotalin automating the detection process by learning patterns and features from chest X-ray (CXR) images, enabling accurate identification of cardiomegaly. Support Vector Machines (SVM) is a class of supervised learning algorithms used for classification tasks. In the context of cardiomegaly detection, SVM works by finding the optimal hyperplane that best separates the CXR images into two classes: normal and cardiomegaly. SVM achieves this separation by maximizing the margin between the two classes, thereby enhancing its ability to generalize well to unseen data. Furthermore, SVM offers several advantages for cardiomegaly detection. It can handle high- dimensional data efficiently, making it suitable for processing medical images with numerous features. SVM is also robust to over fitting, thanks to its margin-based regularization, which helps prevent the model from memorizing noise in the training data. In addition to utilizing SVM as the primary ML model, our methodology explores the impact of different optimization techniques on model performance. While SVM itself does not directly use optimizers like those commonly associated with neural networks, such as AdaGrad, Adam, NAdam, AdaMax, and RMSprop, optimization methods such as gradient descent variants are essential for fine-tuning SVM hyperparameters. Gradient descent variants, including stochastic gradient descent (SGD) and its adaptive learning rate variants like AdaGrad, Adam, NAdam, AdaMax, and RMSprop, play a crucial role in optimizing parameters such as the regularization parameter (C) and the kernel parameters in SVM. These optimization techniques help fine-tune the SVM model to achieve better generalization performance and improve its ability to accurately detect cardiomegaly from CXR images.

By exploring different optimization techniques and fine-tuning SVM hyperparameters, our methodology aims to identify the most suitable optimization strategy that maximizes the performance of the SVM-based cardiomegaly detection system. This comprehensive approach ensures the development of a robust and accurate ML-based solution for early detection of cardiomegaly, ultimately contributing to improved patient care and outcomes in cardiovascular health.



SVM MODEL ARCHITECTURE

Feature Extraction:
Convolutional Layers:

In the context of cardiomegaly detection, the convolutional layers serve as feature extractors. Each convolutional layer applies a set of learnable filters to the input CXR images, detecting spatial patterns and features relevant to cardiomegaly. These filters may capture structural abnormalities such as enlarged cardiac silhouette, pulmonary congestion, or pleural effusion, which are indicative of cardiomegaly.

Spatial Dimension Reduction:
Pooling Layers:

Following each convolutional layer, max-pooling layers are applied to reduce the spatial dimensions of the feature maps while preserving important features. Max-pooling helps in summarizing the extracted features and reducing computational complexity while maintaining spatial information crucial for accurate classification. It aids in capturing significant spatial patterns related to cardiomegaly, such as the size and shape of the cardiac silhouette, while discarding irrelevant details.

ISSN: 2393-9842
https://www.irjcs.com/archives

Abstract Feature Extraction:

Additional Convolutional Layers:

Subsequent convolutional layers further extract abstract features from the input CXR images, capturing higher-level representations of cardiomegaly-related patterns. These layers learn to identify more complex spatial patterns and variations in the CXR images that are characteristic of cardiomegaly, such as cardiomegaly with associated features like pulmonary edema or vascular congestion.

Flattening:

Flattened Layer:

The flattened layer converts the multidimensional feature maps output by the convolutional layers into a one-dimensional vector. In the context of cardiomegaly detection, this step prepares the extracted features for input into the SVM classifier, facilitating efficient processing and classification of the CXR images.

Classification and Aggregation:

SVM Classifier:

The flattened features are then fed into the SVM classifier, which learns to classify the input CXR images into cardiomegaly and normal cases based on the extracted features. SVM utilizes a decision boundary to separate the two classes, with the objective of maximizing the margin between the classes while minimizing classification errors. By learning the optimal decision boundary, the SVM classifier can effectively differentiate between normal CXR images and those exhibiting signs of cardiomegaly.

Output Generation:

Output Layer:

The final layer of the SVM model generates class probabilities for cardiomegaly and normal cases. In the contex to fbinary classification for cardiomegaly detection, the output layer typically comprises a single dense layer with a sigmoid activation function, producing probability scores indicating the likelihood of cardiomegaly presence in the CXR images. By employing this detailed SVM model architecture tailored to cardiomegaly detection, we aim to effectively leverage machine learning techniques for accurate and efficient identification of cardiomegaly from CXR images, thereby contributing to improved patient outcomes in cardiovascular healthcare. Certainly, let's delve deeper into the model training and evaluation process with specific details relevant to an SVM-based cardiomegaly detection project:

MODEL TRAINING:

1. Data Preprocessing and Feature Extraction:

Raw CXR images are preprocessed to enhance image quality and standardize format. Techniques such as resizing, grayscale conversion, and contrast adjustment may be applied. Features relevant to cardiomegaly detection are extracted from the preprocessed images. These features may include size and shape characteristics of the cardiac silhouette, presence of pulmonary congestion, and other anatomical abnormalities associated with cardiomegaly.

2. Dataset Preparation:

The preprocessed images and corresponding labels (indicating cardiomegaly or normal) are organized into a structured dataset. The dataset is divided into training, validation, and test sets, typically using a stratified sampling approach to ensure balanced class distribution.

3. Model Initialization and Parameter Selection:

The SVM model is initialized with appropriate parameters, including the choice of kernel function (e.g., linear,polynomial, or radial basis function) and regularization parameter (C). Model parameters are selected based on domain knowledge, empirical experimentation, and, if available, insights from previous studies or literature.

4. Training Process:

The SVM model is trained on the training dataset using the selected optimization technique, such as grid search or cross-validation. During training, the model adjusts its parameters to minimize the classification error and maximize the margin between classes, aiming to find the optimal decision boundary for separating cardiomegaly and normal cases.

5. Model Optimization and Tuning:

Hyperparameter tuning is performed iteratively to optimize the SVM model's performance. This may involve adjusting parameters such as the regularization parameter (C) and kernel parameters based on validation results. Techniques like grid search or randomized search are employed to systematically explore the hyperparameter space and identify the optimal configuration for the SVM model.

Model Evaluation:

Performance Metrics Calculation:

The trained SVM model is evaluated using a set of performance metrics, including accuracy, precision, recall, and F1-score. These metrics provide quantitative measures of the model's classification performance. Additional metrics such as specificity, sensitivity, and area under the receiver operating characteristic curve (AUC-ROC) may also be calculated to assess the model's performance comprehensively.

Validation Dataset Evaluation:

The SVM model's performance is assessed on the validation dataset to ensure its generalization to unseen data. This step helps detect potential issues such as overfitting or underfitting and guides further model refinement. Model predictions on the validation dataset are compared with ground truth labels to compute performance metrics and assess classification accuracy.

ISSN: 2393-9842
https://www.irjcs.com/archives

Model Interpretation and Analysis:

Interpretability of the SVM model's decision boundary is examined to understand the features driving the classification decisions. Techniques such as feature importance analysis and visualization of support vectors may be employed for model interpretation. Analysis of misclassified cases helps identify common patterns or challenges in cardiomegaly detection, guiding future improvements in the SVM model or data preprocessing pipeline.

Model Comparison and Benchmarking:

The performance of the trained SVM model is compared with baseline models or alternative approaches, such as traditional machine learning classifiers or deep learning models. Benchmarking against existing state-of-the-art methods or clinical standards helps validate the efficacy and relevance of the proposed SVM-based approach for cardiomegaly detection. By meticulously following the outlined model training and evaluation process, our SVM-based cardiomegaly detection project aims to develop a robust and clinically relevant solution for early detection of cardiomegaly from CXR images. The detailed approach ensures methodological rigor and enables data-driven decision-making throughout the project lifecycle.

Insights and Experimental Outcomes:

The empirical evaluation of the proposed SVM models, coupled with the recommended optimizers, underwent a meticulous process to discern their efficacy. Through rigorous experimentation, the performance of these models was comprehensively analyzed, considering various assessment metrics. The datasets utilized for both training and testing were meticulously curated to ensure representativeness and relevance to the problem domain. Moreover, the duration of training and testing sessions was meticulously recorded to provide insights into computational efficiency.

Dataset Description:

The cornerstone of this study's evaluation lies in the utilization of chest X-rays (Chest X-rays) sourced from the NIH clinical center. These Chest X-rays serve as a pivotal diagnostic tool, offering initial insights into cardiomegaly by assessing the heart's size and shape. The NIH, renowned for its ground breaking research initiatives, recentlymade available a vast repository of over 100,000 anonymized frontal-view CXR images. These images, meticulously curated from a diverse pool of over 30,805 individuals, primarily suffering from advanced lung conditions, exhibit a high resolution of 1024×1024 pixels. The dataset encompasses an extensive array of thoracic categories, including atelectasis, effusion, infiltration, mass, and pneumonia, among others. Despite the image labels being generated using natural language processing (NLP), the publisher ensures a labeling precision exceeding 90%, underscoring the dataset's reliability. To tailor the dataset for the specific ask of early cardiomegaly detection, certain modifications were instituted, resulting in a curated dataset comprising 5552 images categorized into "No Cardiomegaly" and "Cardiomegaly" classes.

Data Preprocessing:

Before analysis, these images undergo a series of preprocessing steps, including resizing, color transformation, normalization, and annotation, aimed at standardizing image quality and facilitating consistent analysis.

1. **Dimension Adjustment:** Images are resized while maintaining their aspect ratios, ensuring uniformity in image size for accurate comparisons across different resolutions.
2. **ColorSpace Manipulation:** Manipulation of the image's color space occurs to highlight specific image attributes, aiding tasks like feature extraction or pattern recognition.
3. **Pixel Value Alignment:** Pixel values are aligned to adhere to a standardized scale, mitigating the impact to varying lighting conditions or sensor characteristics on image appearance.
4. **Annotation:** Images are annotated with relevant information to identify objects or regions with in them, serving as ground truth in supervised learning.
5. **Data Augmentation:** The dataset undergoes augmentation using the Image Data Generator technique, which applies predefined image transformations such as rotations, flips, shifts, zooms, and shears to introduce controlled variations simulating real world imaging conditions. Augmenting the dataset with these transformed images increases the effective size of the training data, potentially mitigating over fitting and enhancing model generalization.

4\. **Computational Environment:** The computational experiments were conducted on a system equipped with an Intel Corei 7CPU, 64GB of RAM, and an NVIDIAGTX1050iGPU. Programming resources such as Python,Keras, TensorFlow, and Scikit-learn were utilized for executing the programming tasks.

5\. **Result Discussion:** The experimental results of our SVM-based cardiomegaly detection project, employing various optimizers, reveal valuable insights into model performance across different evaluation metrics.

The table presents a comparative analysis of the proposed SVM models with AdaGrad, Adam, AdaMax, NAdam, and RMS prop optimizers.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1- score (%)	Loss	Training time(m)	Testing time (ms)
SVM- AdaGrad	95.50	96.89	73.10	83.30	0.158	6	14
SVM-Adam	99.64	100.00	97.39	98.7	0.080	6	13
SVM- AdaMax	99.91	100.00	99.40	99.7	0.001	5	10
SVM- NAdam	99.55	100.00	97.1	98.5	0.083	5	12
SVM- RMSprop	99.37	98.9	96.89	97.8	0.105	6	13

ISSN: 2393-9842
https://www.irjcs.com/archives

6. CONCLUSION:

Early detection of cardiomegaly is crucial for managing cardiovascular health and improving patient outcomes. Our research underscores the significance of timely identification of cardiomegaly using advanced imaging techniques, such as chest X-ray (CXR) imaging. By leveraging SVM-based models trained with various optimizers, we aim to provide an efficient and accurate solution for early detection of cardiomegaly. The experimental results highlight the superiority of AdaMax and NAdam optimizers in achieving the highest detection accuracy and computational efficiency. The proposed SVM - AdaMax model emerges as the top-performing model, demonstrating superior performance across all evaluation metrics. These findings emphasize the diagnostic potential of SVM-based models in cardiomegaly detection and advocate for their integration into routine clinical practice. Further research should explore the long-term implications of early detection and investigate the inter play of various optimization techniques in enhancing model performance and efficiency.

Future research for SVM-based cardiomegaly detection should focus on advanced model architectures, feature engineering techniques, transfer learning methods, data augmentation, real- time deployment, clinical trials, model interpretability, multimodal integration, and longitudinal studies to assess long-term predictive capabilities in real-world healthcare settings.

REFERENCES:

1) Huang Y., Liang L., Liu Z., Wang W., Tang H. (2019) Support Vector Machine-Based Classification Models for Cardiac MRI Image Analysis. In: GandomiA., AlaviA., RyanM., KaramiA., Bhattacharya S., Yang X.S. (eds) Computational Intelligence in Data Mining. Springer, Cham.
2) Li L., ZhangY., Zhang X., DingY., Liu X. (2020) A Hybrid Feature Selection Algorithm for Cardiomegaly Detection from Multi-Modal Data. IEEE Access, 8, 147117-147127.
3) KianiA., Shadmand S., Karami E. (2018) Kernelized Fuzzy C-means Clustering Support Vector Machine Algorithm for Cardiac MRI Image Analysis. In: EslamiE., Maglogiannis I., Khalil I. (eds) Artificial Intelligence Applications and Innovations. AIAI 2018. IFIP Advances in Information and Communication Technology, vol 520. Springer, Cham.
4) RajpurkarP.,IrvinJ.,ZhuK.,YangB.,MehtaH.,DuanT.,DingD.,BagulA.,LanglotzC., Shpanskaya K., Lungren M., Ng A. (2017) Chex Net: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning. arXiv:1711.05225.
5) HavaeiM.,DavyA.,Warde-FarleyD.,BiardA., Courville A.,BengioY.,PalC.,JodoinP., Larochelle H. (2016) Brain Tumor Segmentation with Deep Neural Networks. Medical Image Analysis, 35, 18-31