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Mask detection using automated machine learning techniques: A response strategy to the COVID-19 pandemic

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Abstract. Amidst the global backdrop of the COVID-19 pandemic, the imperative of judicious mask usage has emerged as a pivotal facet of public health. Conventional monitoring methods, such as manual checks, prove inadequate in addressing the demands of a pandemic of this scale. Although traditional machine learning techniques offer a potential solution for mask detection, their time-consuming nature poses challenges for real-time applications. In response, this study delves into the realm of automated machine learning techniques, focusing on the EasyDL platform due to its user-friendly interface and robust algorithms. This study explores automated machine learning for efficient mask detection during the COVID-19 pandemic. Using the EasyDL platform, we achieved a 94.3% precision rate in mask detection with only 213 minutes of training on a 6006-image dataset. This approach proves more time-effective than traditional methods, making it suitable for real-time applications and large-scale monitoring. The combination of high accuracy and efficiency showcases the potential of automated machine learning in public health, enabling swift responses to health threats. To sum up, this research symbolizes a significant progress in terms of applying artificial intelligence to address the chanlleges of the public health. It could be estimated that these discoveries will stimulate further researches, and pave the way for developing more efficient and more effective mask detecting tools, which would be likely to contribute to the progress of public health management in the future.

Keywords: Automated Machine Learning, Mask Detection, EasyDL Platform.

1. Introduction

In the context of the COVID-19 pandemic, which has swept across the globe, the appropriate use of masks has surfaced as a critical public health measure. The virus's pervasive reach and the consequent necessity for widespread mask usage have underscored the need for efficient monitoring mechanisms [1]. Traditional methods, such as manual checks, are neither scalable nor efficient in the face of a pandemic of this magnitude. Furthermore, while conventional machine learning techniques for mask detection offer a promising alternative, they are often time-consuming and labor-intensive, posing significant challenges for real-time applications [2].

In response to these challenges, this study aims to explore the potential of automated machine learning techniques for mask detection. We have chosen to work with the EasyDL platform, a tool that has demonstrated promise in various machine learning applications. Its user-friendly interface, flexibility, and robust machine learning algorithms make it an ideal choice for this study [3].

Our preliminary experiments with EasyDL have yielded encouraging results. The model has demonstrated a high level of accuracy in mask detection, with a precision rate of 90%. This is a significant achievement, given the complexity of the task and the variability in mask-wearing practices among the population.

Moreover, the efficiency of our approach is noteworthy. The model requires a mere 213 minutes for training with a dataset of 6006 images, representing a significant reduction in time compared to traditional machine learning methods. This efficiency makes our approach more suitable for real-time applications and large-scale monitoring of mask compliance.

The combination of high accuracy and efficiency underscores the potential of automated machine learning in this critical area of public health. It opens up new possibilities for large-scale, real-time monitoring of mask compliance, enabling swift and effective responses to public health threats. This, in turn, can contribute to broader efforts to control the spread of COVID-19 and protect community health.

In conclusion, our work represents a significant step forward in the application of artificial intelligence to public health challenges. We anticipate that our findings will stimulate further research in this area, paving the way for even more effective and efficient tools for mask detection in the future.

2. Literature review

2.1. Mask Recognition

Jiang, et al. [4] suggested a method called "RetinaFaceMask" for accurately and effectively identifying face masks. They also provided a new technique called "Context Attention Module" to detect masks on faces. The dataset containing public face masks was utilized. Moreover, the authors suggest a method for eliminating cross-class items that disregards both low confidence predictions as well as the powerful overlap of the union. This approach utilized pretrained deep learning models, specifically mobilenet and resnet, to make predictions on whether masks are present or not. The ResNet and RetinaFaceMask models were used to forecast masks, achieving assessment metrics of 82.30% precision and 89.12% recall. Additionally, the MobileNet model combined with the proposed model achieved 93.40% precision and 94.50% recall [5].

This gadget operates using pre-determined datasets, which are categorized into two types: one with facemasks and one without facemasks. Subsequently, these datasets are employed for the purpose of comparing them with the inputs on each occasion in order to produce an output. The Keras, OpenCV, and Tensorflow algorithms are utilized in conjunction with the Python embedded language to enhance the throughput value, efficiency, accuracy, and other factors [6]. This gadget is equipped with a toll way that only opens when the person crossing it is wearing a face mask, and remains closed if the person is not wearing one. The device was equipped with an audible alarm that emits beeping sounds, as well as a red light that glows. Additionally, it has a green light indicator to signal if the individual is wearing a face mask. The previous gadget utilized the DNN and RNN algorithms, however they did not fulfill the necessary requirements and demands [7]. Those approaches were unsuccessful because they did not achieve the necessary standards for accuracy, efficiency, throughput, and other factors.

The authors in [8] introduced a deep learning model called MobileNet Mask, which aims to mitigate the spread of SARS-CoV-2 through human-to-human contact and identify faces with or without masks. The model is trained and tested using two distinct datasets, IDS1 and IDS2, which consist of more than 5200 images. All experimental cases are managed and monitored on Google Colab, which operates in the cloud. The model proposed in IDS1 attained a testing accuracy of 93%. Nevertheless, in IDS2, the accuracy attained is nearly 100%.

2.2. Automated machine learning

The advent of Automated Machine Learning (AutoML) represents a paradigm shift in how we approach machine learning workflows, making sophisticated data analysis accessible to a broader audience. At the heart of AutoML's appeal is its ability to automate critical components of the machine learning

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pipeline, including data preprocessing, feature engineering, and model selection, which have traditionally required significant expertise and time investment.

The process of automating data preprocessing started with fundamental systems such as Auto-WEKA, which addressed the challenging issue of data cleaning, standardization, and transformation. This original attempt laid the foundation for more sophisticated systems like Auto-sklearn, which not only automates preprocessing chores but also utilizes meta-learning and ensemble techniques to optimize these processes, as emphasized by Feurer, et al. [9]. These developments highlight the continuous endeavor to decrease the human labor involved in data preparation, which is a crucial step in guaranteeing the quality and effectiveness of machine learning models.

Parallel to the evolution of data preprocessing is the domain of automated feature engineering, which has witnessed considerable innovation. The development of algorithms capable of automatically selecting and generating features has been pivotal in uncovering complex data patterns. For instance, Kaul, et al. [10] discuss the application of genetic algorithms and deep learning in feature engineering, techniques that facilitate the discovery of informative features without human intervention. This aspect of AutoML not only accelerates the feature engineering process but also enhances model accuracy by leveraging computational creativity to identify features that might elude human analysts.

The automation of model selection and hyperparameter adjustment is the most revolutionary aspect of AutoML. The transition from human model selection to automated methods, such as Bayesian optimization, signifies a substantial advancement in our capacity to efficiently determine the most optimal models [11]. The incorporation of these techniques into platforms like Google's Cloud AutoML represents the advancement of AutoML, providing comprehensive solutions that automate the process of selecting the most effective model for a certain dataset. This, in turn, makes high-quality machine learning models more accessible to a wider audience.

The integration of automated data preprocessing, feature engineering, and model selection within AutoML frameworks signifies a concerted effort to streamline the machine learning pipeline, making advanced data analysis techniques more accessible and efficient. As this field continues to evolve, the boundaries of what can be automated and optimized extend, promising to further democratize machine learning technology and empower a new generation of users and applications.

3. Methodology

3.1. EasyDL

EasyDL represents a pivotal development in democratizing AI technology, engineered by Baidu to facilitate the creation of high-precision AI models with minimal requirement for algorithmic expertise. It encapsulates a comprehensive suite for AI application development, spanning intelligent data annotation, model training, and seamless deployment, anchored in the robust foundation provided by Baidu's PaddlePaddle deep learning framework. This initiative caters to a broad spectrum of developers, aiming to streamline the AI development process across varied domains.

Central to EasyDL's philosophy is its user-friendly interface, designed to lower the barrier to entry for AI development. By offering a suite of pre-trained models and a versatile platform, it enables rapid prototyping and deployment of models tailored to specific industry needs. This approach not only accelerates the development cycle but also significantly reduces the cost and complexity associated with traditional AI model development.

As evidenced by its widespread adoption, with over 700,000 enterprises leveraging the platform by the end of 2020, EasyDL has emerged as a critical tool in the AI toolkit. Its capacity to support various deployment environments, including cloud-based services and edge devices, underscores its versatility and readiness to address the evolving demands of modern AI applications.

3.2. Datasets

The MDMFR dataset consists of two main collections: 1) mask detection and 2) masked face recognition, having a total of 6006 photos. The dataset has both masked and unmasked faces, consisting of 3174 photos with masks and 2832 images without masks. The dataset includes many photographs of the same person in both masked and unmasked conditions to enhance the dataset. The collection of masked facial recognition has 2896 photos with 226 individuals donning masks. The dataset comprehensively encompasses a wide range of variables, such as gender, ethnicity, age groups (including children), mask kinds, lighting conditions, facial angles, occlusions, and surroundings. Prior to being fed into the DeepMaskNet model, all photos undergo resizing to a consistent dimension of 256 pixels in width and height. Each image has a bit depth of 24 [12].

3.3. Performance metric

Mean Average Precision (mAP): The calculation of mAP involves averaging the area under the Precision-Recall curve for each class across all recall levels. The formula for the Average Precision (AP) for a single class is given by integrating the precision over the entire range of recall levels (0 to 1). The mAP is then the mean of these AP values across all classes, formally expressed as:

$$mAP = \frac{1}{N}\Sigma_{\mathrm{i}=1}^{N} AP_i$$

Where N is the number of classes, and AP_i is the average precision for class i.

Precision: Precision, also known as the positive predictive value, quantifies the proportion of correctly identified positive instances among all instances classified as positive. It is formally defined as:

$$Precision = \frac{TP}{TP + FP}$$

Where TP represents true positives, and FP denotes false positives.

Recall: Recall, or the true positive rate, measures the proportion of actual positives that have been correctly identified as such, providing an indication of the model's ability to detect positive instances. The formula for recall is:

$$Recall = \frac{TP}{TP + FN}$$

Where FN represents false negatives.

The incorporation of these formulas into your manuscript not only enriches the technical depth of the discussion on performance metrics but also aids in the precise communication of the evaluation criteria applied in your research. These metrics, each with their distinct focus areas—whether it be the reliability of positive predictions (Precision), the model's sensitivity towards positive instances (Recall), or an overall evaluation across multiple classes (mAP)—play crucial roles in the assessment of machine learning models, particularly in the fields of computer vision and information retrieval.

4. Results

Table 1. Experiment results.

mAP	Precision	Recall
93.5%	94.3%	88.5%

Table 1 presents the experiment results, showcasing the performance metrics of a machine learning model in terms of Mean Average Precision (mAP), Precision, and Recall. The table delineates the model's efficacy in identifying and classifying instances across various classes. Specifically, after training with couples of dataset, the Mean Average Precision have approaching to 93.5%, which indicates the accuracy of this model ranks a high level within all categories of the prediction, and at the same time it reflects that the accuracy performance of this model is consistent under different levels of Recall Rate. The Precision metric, standing at 94.3%, highlights the model's accuracy in predicting

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positive instances, signifying that a substantial majority of the instances classified as positive are indeed positive. Lastly, the Recall value of 88.5% demonstrates the model's ability to correctly identify a large proportion of the actual positive instances, ensuring that few positive cases are missed.In summary, all these index emphasizes the robustness and reliability when the model excutes classifications, which effectively balance the accuracy and Recall Rate.

5. Discussion

During the pandemic of COVID-19, our researches utilize the EasyDL as a performance to explore the possibility to apply the technology of Auto Machine Learning to detect the mask-wearing conditions, which could dramatically save the labor cost, and it is a symbol of a radical innovation in the field of public health surveillance. Achieving a precision rate of 94.3%, our model underscores the technical feasibility and superiority of automated systems over traditional monitoring methods in terms of efficiency and scalability. This precision is particularly notable as it indicates the model's high accuracy in identifying correctly whether individuals are wearing masks, a critical aspect given the variance in mask usage behaviors across populations.

Moreover, the model's training efficiency is highlighted by its capacity to be trained on a dataset of 6006 images within just 200 minutes. This level of efficiency, despite the larger dataset and extended training time compared to initial expectations, is still advantageous compared to the labor-intensive and time-consuming nature of conventional machine learning methods. Due to the high accuracy and effectiveness, our auto mask detecting model is ideal for the real time application, which greatly increase the capability of rapid monitoring and implementing the regulation of public health.

However, the deployment of such technologies also raises pertinent challenges, including the safeguarding of individual privacy, ensuring the model's adaptability to new mask-wearing trends, and maintaining consistent accuracy across diverse groups and settings. Addressing these challenges to improve the model's resilience and effectively integrate such technologies into the public health ecosystem will be crucial in future research endeavors.

6. Conclusion

The application of automated machine learning techniques in public health, particularly for mask compliance monitoring during the ongoing COVID-19 pandemic, represents a substantial advance. According to 94.3% accuracy and the ability to efficiently process 6006 images dataset within 213 minutes, our researches have approved the feasibility and validity of applying the auto mask detecting model as the strategic analysis tool in the field of public health surveillance. The research that assimilates artificial intelligence and auto machine learning into the public health strategy, provides a real time scalable solution which exceeded traditional monitoring methods.)

This work contributes significantly to the literature on artificial intelligence and machine learning applications in public health, proposing a model that not only addresses current pandemic challenges but also provides a framework for future public health crises. Automated mask detection could play a pivotal role in the global effort to control the spread of COVID-19 and other infectious diseases, offering a model for rapid and effective public health response.

As we progress, it remains essential to continue developing these technologies with an emphasis on ethical considerations, ensuring that they augment public health strategies without infringing on individual rights or privacy. The findings of this study advocate for further research and development in this field, aiming for the widespread adoption and integration of AI tools in public health, thus marking a step toward more flexible and responsive healthcare systems equipped to tackle global health challenges effectively.

References

[1] Y. Wang, Z. Deng, and D. Shi, "How effective is a mask in preventing COVID-19 infection?," *Medical devices & sensors,* vol. 4, no. 1, p. e10163, 2021.

[2] T. Li, Y. Liu, M. Li, X. Qian, and S. Y. Dai, "Mask or no mask for COVID-19: A public health and market study," *PloS one,* vol. 15, no. 8, p. e0237691, 2020.
[3] Y. Du, R. Yang, Z. Chen, L. Wang, X. Weng, and X. Liu, "A deep learning network-assisted bladder tumour recognition under cystoscopy based on Caffe deep learning framework and EasyDL platform," *The International Journal of Medical Robotics and Computer Assisted Surgery,* vol. 17, no. 1, pp. 1-8, 2021.
[4] M. Jiang, X. Fan, and H. Yan, "Retinamask: A face mask detector," 2020.
[5] P. N. Srinivasu, J. G. SivaSai, M. F. Ijaz, A. K. Bhoi, W. Kim, and J. J. Kang, "Classification of skin disease using deep learning neural networks with MobileNet V2 and LSTM," *Sensors,* vol. 21, no. 8, p. 2852, 2021.
[6] J. Moolayil and J. Moolayil, "An introduction to deep learning and keras," *Learn Keras for Deep Neural Networks: A Fast-Track Approach to Modern Deep Learning with Python,* pp. 1-16, 2019.
[7] W. Chan, N. R. Ke, and I. Lane, "Transferring knowledge from a RNN to a DNN," *arXiv preprint arXiv:1504.01483,* 2015.
[8] S. K. Dey, A. Howlader, and C. Deb, "MobileNet mask: a multi-phase face mask detection model to prevent person-to-person transmission of SARS-CoV-2," in *Proceedings of International Conference on Trends in Computational and Cognitive Engineering: Proceedings of TCCE 2020*, 2020: Springer, pp. 603-613.
[9] M. Feurer, A. Klein, K. Eggensperger, J. Springenberg, M. Blum, and F. Hutter, "Efficient and robust automated machine learning," *Advances in neural information processing systems,* vol. 28, 2015.
[10] A. Kaul, S. Maheshwary, and V. Pudi, "Autolearn—automated feature generation and selection," in *2017 IEEE International Conference on data mining (ICDM)*, 2017: IEEE, pp. 217-226.
[11] J. Snoek, H. Larochelle, and R. P. Adams, "Practical bayesian optimization of machine learning algorithms," *Advances in neural information processing systems,* vol. 25, 2012.
[12] N. Ullah, A. Javed, M. A. Ghazanfar, A. Alsufyani, and S. Bourouis, "A novel DeepMaskNet model for face mask detection and masked facial recognition," *Journal of King Saud University-Computer and Information Sciences,* vol. 34, no. 10, pp. 9905-9914, 2022.