Journal of Theoretical and Applied Information Technology
15th December 2023. Vol.101. No 23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

MULTITASK LEARNING FOR GENDER IDENTIFICATION AND AGE GROUP BASED ON THE MANDIBLE ON PANORAMIC RADIOGRAPHS

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ABSTRACT

Forensic odontology is commonly applied for victim identification using comparing antemortem and postmortem dental radiographs. However, in cases where a victim's teeth are incomplete or missing, the mandible bone can also be used as a robust alternative for victim identification. Gender identification and age estimation are two tasks to assist in victim identification. For multiple related tasks, the multitask learning (MTL) approach has been proven to enhance generalization performance by concurrently learning the multiple related tasks and leveraging useful information across the tasks. Therefore, in this study, we propose an MTL approach for gender identification and age group based on the mandible. We propose a model, namely the mandible radiographs MTL model, that takes panoramic radiographs of the mandible as input. We built a dataset, namely the mandible radiographs dataset comprising 120 patients' panoramic radiographs of the mandible collected from Universitas Airlangga Dental Hospital, Surabaya, Indonesia, then augmented to 600 images. The experimental results show that the augmented mandible radiographs MTL model achieved the best performance for gender identification with a mean accuracy of 99.7% and an age group of 99.5%. Our research proposal is more practical because 1 model directly produces two outputs (gender and estimated age), so it is time efficient in creating models or testing.

Keywords: *Multitask Learning, Mandibular Panoramic Radiographs, Dental Panoramic Radiographs, Gender Identification, Age Group.*

1. INTRODUCTION

Indonesia lies in the Pacific Ring of Fire and consists of many volcanic mountains. This causes the country to be prone to natural disasters. Furthermore, Indonesia is also vulnerable to man-made disasters including landslides and floods due to activities such as deforestation. These disasters may cause a large number of fatalities. Therefore, victim identification is necessary to inform family members of the victims. However, due to the large number of fatalities, victim identification becomes a very challenging task.

Gender identification and age estimation are applied in forensic medicine to assist in person identification and can be carried out by analyzing the human skeleton. Victim identification in cases of mass disasters generally follows the INTERPOL standards, in which there are two types of identification methods, namely primary and secondary methods [1]. Primary methods of identification include fingerprint, dental, and DNA analysis [2]. While secondary methods of identification include individual description (tattoos, scars, and gender), medical findings, and examining items found on the body. The identification process is vital in analyzing the cause of death and providing closure to the family of the victim.

Forensic odontology is the application of dental knowledge for person identification in a legal context. When the body of a deceased person is still intact, the identification process is carried out conventionally by means of using facial and body features, items on the body, certificates, documents, identity cards, and fingerprints. However, in cases where the corpse is either rotten, dismembered, burned, or only skeletal remains are found, identification using conventional methods is very

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

difficult or even impossible. In such cases, forensic odontology methods can be applied for person identification with the use of dental evidence [3].

Victim identification using forensic odontology can be carried out by comparing the antemortem and postmortem radiographs [4]. Previous studies have carried out gender identification and age estimation by examining teeth in radiographic images [5], [6]. However, in cases where the teeth of a victim are incomplete or missing, the mandible bone can also be used for victim identification. The mandible is a robust alternative to teeth as it is one of the strongest and largest facial bone [7].

Traditional victim identification methods require human experts to perform analysis of the bones with the assistance of measuring instruments or software applications [8], [9]. These methods rely on the skills and experience of experts. The disadvantage of this is that in cases where there is a large number of victims to be examined, the human experts may experience fatigue leading to less accurate results. To remedy this problem, machine learning methods have been used to examine panoramic radiographic images of bones such as the mandible [10].

Based on the issues above, we propose a model for automatic gender identification and age group. The model takes as input digital panoramic radiographs of the mandible. The proposed models adopt an MTL approach and perform the two tasks, namely gender identification and age group, simultaneously. MTL is a paradigm that aims to enhance generalization performance by concurrently learning multiple related tasks and leveraging useful information across the tasks. MTL models have been shown to produce highly satisfactory results compared to single-task learning models with prediction accuracies of over 90% [11].

The reason that identification is needed in Indonesia is because disasters often occur with large numbers of victims. The process of identifying a victim in a condition where only bones or teeth are left, then for identification you can use bones or teeth. The best bone for identifying gender and age can be the mandible bone. The identification process for large numbers of victims requires a high level of concentration and accuracy, especially if you have to measure many parameters. So an automatic tool is needed to identify gender and age.

The contributions of this research are as follows: a) Building datasets, namely the 120 patients mandible radiographs dataset comprised of panoramic radiographs of the mandible collected from Universitas Airlangga Dental Hospital, Surabaya, Indonesia, then augmented to 600 mandible radiographs panoramic image. b) Building MTL models for gender identification and age group. The model takes as input panoramic radiographs of the mandible. c) Evaluating the performance of the proposed MTL models for gender identification and age group.

2. RELATED WORK

Machine learning models often focuses on completing a single task. They require a large amount of labelled data to achieve high generalization performance. In tasks where labelled data is scarce, this becomes a problem. In many real-world problems, information contained in one task may serve as useful information to other tasks within the same domain [12]. MTL has been widely applied on text data and images to perform various tasks in several different fields due to its efficiency and effectivity in concurrently completing multiple tasks using only one shared model. The principle of MTL is inspired by the learning ability of humans, in which existing knowledge is reused to perform related tasks [13].

There have been previous studies on MTL where features are jointly extracted for multiple related tasks to leverage shared information between tasks. [14] Proposed an MTL model that performs the detection of four age-related macular degeneration (AMD) features from color fundus images and subsequently used in combination for the classification of AMD severity. [15] Proposed an MTL model that extracts features from images for learning three related vision tasks, namely semantic segmentation, surface normal estimation, and depth estimation. [16] Proposed an MTL model that extracts five features of hip osteoarthritis on radiographs for simultaneous severity grading of these features. [17] Proposed an MTL model that extract multi-scale features from images for learning three related vision tasks, namely semantic segmentation, edge detection, and depth estimation. [18] Proposed an MTL model that extracts features of red mullet fish from otolith images for learning two related tasks, namely fish length prediction and fish age estimation.

MTL has been applied in several different fields of research. In the geographical science domain, MTL models have been proposed for the purpose of flow prediction throughout a spatio temporal network [19], multi-location prediction of monthly precipitation on geospatio-temporal data [20], and hyperspectral image classification [21]. In the medical domain, MTL has been applied for learning a personalized medical model for each patient [22] and to overcome missing values in patient data for prediction of disease progression [23]. In the psychological domain, MTL has been applied for simultaneous detection of personality traits and emotion due to the strong correlation between the two variables [24], and also predicting the mental and physical condition of a person by learning a personalized model for each person [25].

Machine learning models require large and high-quality datasets to achieve high performance. However, labelled data may not always be available in large quantities. Furthermore, collecting quality labelled data is also time-consuming and expensive. MTL has been applied in tasks where only a small number of labelled data is available for learning shared representations to improve generalization [26], [27]. Moreover, the application of MTL has also been shown to produce satisfactory results when less data is used for training to reduce storage in cases where the number of tasks is large [28]. Many researchers have applied the MTL approach and achieved great results for various tasks in many different domains. Table 1 describes the research gaps identified by gender and age. In previous studies, identifying gender and age estimation age was carried out separately [29]. In previous research, the data objects used for identification were radiographic images of teeth in the upper and lower jaw. Meanwhile, those who use the mandible in panoramic radiography must first measure several parameters in the mandible [10], [30]. Therefore, we propose a MTL approach for gender identification and age group on panoramic radiographs of the mandible.

Table 1: State of the Art Gender and Age Identification

Dataset and research object	Method	Result
Panoramic dental X-ray images [5], [6]	Multilayer Perceptron Neural Network	Panoramic dental images of 150x150 size are taken for each pixel by dividing it into sub-subs for the feature extraction process. The feature values are made into an identification model. The accuracy evaluation results reach 99.9%.
Panoramic radiographs from a radiological service [10]	Machine Learning	Panoramic radiographic image measured mandibular parameters. The measurement results were made into a machine-learning model for gender identification.
Orthopantomograms (OPTs) imaged at the dental medicine center (UZM) at the University Hospital Dresden (UKD) [31]	Bayesian CNN	Dental panoramic radiographic image of age identification.
Panoramic radiographs [30]	ANN	Panoramic radiographic image measured mandibular parameters. The measurement results create a gender identification model with the ANN method. The highest accuracy result of 75%.
Panoramic radiographs images from Spanish Caucasian subjects aged between 4.5 and 89.2 were provided to us by the School of Medicine and Dentistry, Universidade de Santiago de Compostela (Spain) [29]	DANet and DASNet	Panoramic dental images were made using the CNN model for age identification and gander.
Panoramic radiographs [32]	Machine Learning (Distance)	Panoramic radiographic image measured mandibular parameters. The measurement results are used to search for identification by calculating the similarity distance.
The PDR (Panoramic Dental Radiographs) were obtained from March 2003 to September 2018 in three hospitals (West China School/Hospital of Stomatology; Chengdu West China Dental	CNN	Panoramic dental images were made using the CNN model for identification based on the most similar matches.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Implantology Hospital; XINQIAO Stomatology) [33]		
Panoramic radiographs [34]	Deep Learning	Label and recognize teeth with deep learning.
Dental periapical X-rays is provided by Peking University School and Hospital of Stomatology [35]	Mask-CNN	Perform dental identification and box bonding using the CNN method.
Dental panoramic X-ray images [36]	CNN	Search for suitable teeth for identification using the CNN method and transfer learning.
Panoramic dental x-ray image [37]	Deep Learning	Panoramic dental images are age grouped into (20-30, 30-40, 40-50, 50-60, 60-70, and 70 years and over), then their ages are estimated using deep learning.
Our Proposal Mandible panoramic radiographs	Multitask Learning	The mandibular image on panoramic radiography was modelled for gender identification. The estimated age groups were five, group one (19-29), group two (30-39), group three (40-49), group four (50-59), and group five (60-70) with deep learning multitask learning method.

3. METHOD
3.1 Dataset

The radiographs used in this study were collected from Universitas Airlangga Dental Hospital, Surabaya, Indonesia. Radiologists confirmed the quality of the radiographs. Radiologists were responsible for selecting the radiographs based on selection criteria. The inclusion criteria are as follows: the patient's age is between 19-70 years, the quality of the radiograph is good, and the anatomy of the mandible is visible on the radiograph. While the exclusion criteria are as follows: undefined mandibular appearance, for example, the condyle and coronoid areas overlap with other anatomical features, and mandible abnormalities are present, for example, growth disorders, tumor/cyst, or broken mandible. The mandible radiographs dataset is 120 patients comprised of panoramic radiographs of the mandible (with a size of 224x224) that radiologists selected. The mandible radiographs dataset has been augmented to training data 600 and 120 testing original data. Figure 1 shows an example of an image in the dataset. Ethical testing was conducted on the data by The Health Research Ethics Feasibility Commission (KKEPK), Faculty of Dentistry, Universitas Airlangga, Surabaya, with certificate number 651/HRECC.FODM/VIII/2022.

Figure 1: Example of an Image in the Mandible Radiographs Dataset

Table 2: Data Original for Testing

Age Group (Year)	Male	Female	Total
19-29	15	14	29
30-39	11	11	22
40-49	12	10	22
50-59	10	11	21
60-70	13	13	26
Total	61	59	120

Our dataset includes 120 patients aged 19-70 years and is grouped into five based on research [38]. The distribution of the first group is 19-29 years old, the second group is 30-39 years old, the third group is 40-49 years old, the fourth group is 50-59 years old, and the fifth group is 60-70 years as shown in Table 2. The original dataset of 120 panoramic radiographic mandibular images was used for model testing, and data training was augmented into 600 images, as shown in Table 3. The augmentation process was refined using the CLAHE (Contrast Limited Adaptive Histogram Equalization) method, median filter, and blurred. Data augment 600 panoramic radiographic mandibular images were used as a training model.

Table 3: Data Augmentation for Training

Age Group (Year)	Male	Female	Total
19-29	75	70	145
30-39	55	55	110
40-49	60	50	110
50-59	50	55	105
60-70	65	65	130
Total	305	295	600

3.2 The Proposed multitask learning model

In this study, we propose a model that takes as input panoramic radiographs of the mandible (shown in Figure 2). The mean accuracy metric was used to evaluate the performance of the models for age group and gender identification. The formula for mean accuracy is shown in Equation 1. Gender identification and age group are significant issues in the medical domain. Anatomical regions of the mandible that experience morphological changes during growth can be used for gender determination [38], [39]. Gender identification and age group using investigating mandibular morphology have produced high accuracy. Figure 2 shows the architecture of the proposed MTL models for gender identification and age group. Previous research has shown that the MTL approach can be applied to simultaneously learn two tasks and achieve significant results [40]. Furthermore, for small scientific datasets such as the dataset used in this study, using four hidden layers in an MTL model is optimal [27]. Therefore, the proposed MTL models in this study possess four hidden layers. The training model consists of weight vector values that change according to the data pattern of each iteration in the learning process. Binary cross-entropy is used as the loss function for the gender identification task, while sparse cross-entropy is used as the loss function for the age group task.

$$accuracy = \frac{\sum_{i=1} y_i = \hat{y}_i}{N} \quad (1)$$

where y is the actual label and $\hat{y}$ is the predicted label.

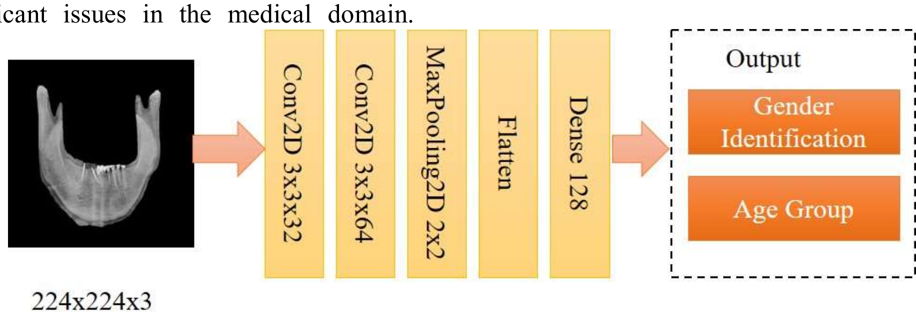


Figure 2: Mandible Radiographs MTL Model for Gender Identification and Age Group

4. RESULTS

Table 4 shows the evaluation results of the proposed models for two tasks, namely gender identification and age group. The models were trained and tested several times. We investigated using three different optimizers: The Rooted Mean Square Propagation (RMSprop), SGD, and Adam optimizer. The results indicate no significant difference between using the RMSprop optimizer and the Adam optimizer. Furthermore, binary cross entropy was used as the loss function for the gender identification task, while sparse cross entropy was used as the loss function for the age group task. Mean accuracy was used as the evaluation metric for the gender identification and age group tasks. It can be seen from Table 4 that the highest mean accuracy of the mandible radiographs MTL model was 1%, with the use of the RMSprop, and Adam optimizer. We investigated the use of different numbers of filters for the convolutional layers in

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the mandible radiographs MTL model to enhance its performance. It was found that using a different number of filters did not increase the model's accuracy. Figure 3 shows the training accuracy and loss for the proposed models.

A comparison of the performance of the evaluation results of the CNN transfer learning model is shown in Table 5. In Table 5, each pretrained model is used to train the case of its own gander identification and its own age estimation. The advantage of our model compared to using pretrained is that one model directly produces two outputs (gender and age) so it is more time efficient. Data from 600 images were trained using transfer CNN to create gender identification and age estimation models independently, and we train 30 epochs, each epoch reads 400 images. In previous research, the gender and age identification processes were made independently. In previous research, the data used were radiographic images of all the teeth in the upper and lower jaw, including the DENT-net model for automating identification with the matching process having an AUC evaluation value of 0.996 [33], creating two DANet models for age identification with an absolute error evaluation value of 0.75 and DASNet for gender identification with an AUC evaluation value of 0.92 [29], and used the model transfer learning CNN (DenseNet201, InceptionResNetV2, ResNet50, VGG16, VGG19, Xception) to identify age with an R^2 evaluation of 0.8439 [37]. The model's weakness in previous research was creating two outputs (identification of gender and age) because it had to be trained twice so that the time would take longer. Previous research that used measurements of several parameters in the mandible had an accuracy evaluation level of 0.891 using the Neural Network method [10], accuracy of 0.75 using the ANN method [30], 85% level of truth by matching with antemortem data based on the closest distance [32].

The model we propose is Multitask-Learning on panoramic radiographic mandibular images, which is superior to other models. The proposed mandible radiographs MTL model achieved the best performance for gender identification and age group compared to the transfer learning methods. The proposed mandible radiographs achieved a significant mean accuracy, a gender identity of 99.7%, and an age group of 99.5%. However, the proposed mandible radiographs model has the advantage of completing two tasks simultaneously, which reduces time and storage. Furthermore, we compared the performance of the proposed mandible radiographs MTL model to deep learning models transfer learning. The results confirm that the proposed mandible radiographs MTL model achieved the best performance compared to the previously proposed deep learning models.

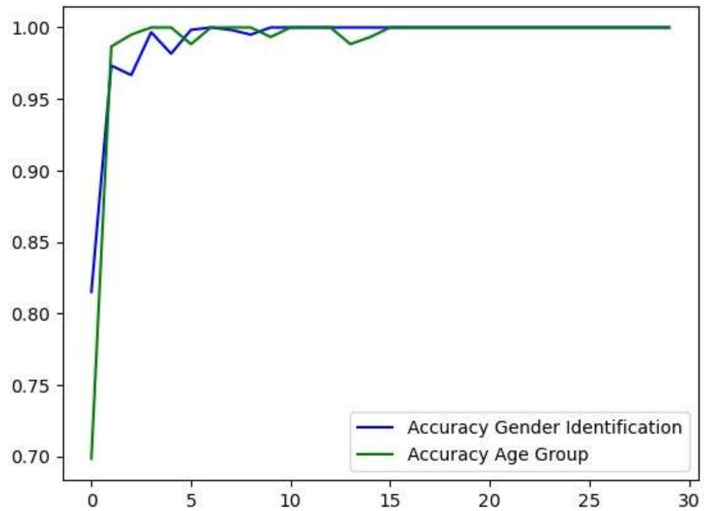
Table 4: Evaluation Testing Results of the Proposed Models

Optimizer (learning rate=0.001)	Mean Accuracy (Gender Identification)	Mean Accuracy (Age Group)
RMSProp	100	100
Adam	100	99.2
SGD	99.2	99.2

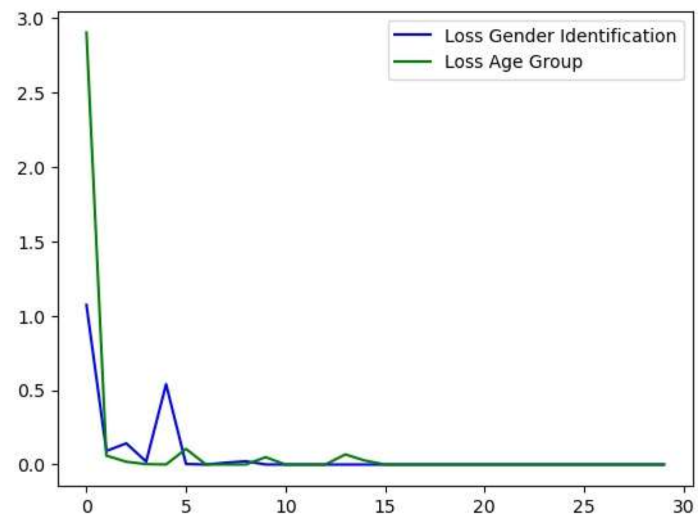
Table 5: Performance Comparison of Different Methods

No	Methods	Mean Accuracy (Gender Identification) %	Mean Accuracy (Age Group) %
1	DenseNet121	90.8	59.2
2	DenseNet201	92.5	60.8
3	InceptionResNetV2	60.0	30.8
4	ResNet50	95.0	87.5
5	VGG16	96.7	93.3
6	VGG19	98.3	91.7
7	InceptionV3	82.5	42.0

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195



(a)



(b)

Figure 3: Mandible Radiographs MTL the Training (a) Accuracy (b) Loss

5. CONCLUSION

This study proposes an MTL approach for gender identification and age group based on the mandible. We apply an MTL approach because the gender identification and age group tasks are related. Using an MTL approach, information from both tasks can be leveraged to enhance generalization performance for small datasets. We built a dataset of radiographs panoramic of the mandible that augment. Furthermore, we propose the MTL model; the model takes as input radiographs of the mandible. We compared the proposed models with state-of-the-art models for gender identification and age group tasks. The experimental results indicate that the proposed mandible radiographs MTL model was able to achieve a significant mean accuracy of 99.7% for the gender identification task and was able to outperform the other state-of-the-art models in the age group with a mean accuracy of 99.5%.

For future research, we suggest collecting and testing the performance of the proposed models with larger amounts of data. Furthermore, the proposed models can be further tested for completing the two tasks based on other human body parts.

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