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Article

ARTIFICIAL INTELLIGENCE IN MARKETING PRACTICES: GAIT BASED AGE ESTIMATION USING CNNS

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Abstract: . Every day, new developments in technology significantly influence business activities, especially in marketing. This study explores the application of artificial intelligence to marketing by evaluating how different Convolutional Neural Network (CNN) architectures perform in gait-based age estimation, a key biometric feature for personalized marketing strategies, such as targeted advertising and real-time consumer profiling. Using Gait Energy Image (GEI) representations and the OULP-Age dataset, we benchmarked models including EfficientNetB7, RegNetY, CrossVIT, InceptionV3, and ResNet152. Among these, CrossVIT achieved superior performance with a Mean Absolute Error (MAE) of 2.69 years, outperforming all previously published methods, which typically report MAEs in the 3.7–8.4 range. These findings demonstrate the potential of gait-based deep learning approaches not only for advancing intelligent, real-time marketing solutions but also for contributing to the broader field of computer vision, illustrating how advanced neural architectures can effectively address complex behavioral biometric tasks in real-world scenarios.
Keywords: Artificial Intelligence, Marketing, Consumer, Gait, Age Estimation, Convolutional Neural Networks

1. Introduction

With the emergence of digitalization, significant changes have occurred in the world. The ongoing changes around the world have begun to affect the activities of businesses significantly. Artificial intelligence (AI) along with the related concepts such as machine learning and deep learning which have started to be on the agenda frequently with digitalization, especially in recent years, has brought about significant transformations in business activities. As a matter of fact, nowadays, AI is being used in different sectors like manufacturing, education, law and business etc. for different purposes such as analyzing, comprehending and in decision making [13]. As the use of AI becomes more widespread, it is seen that it has started to gain an important place in marketing activities [30]. The use of AI has paved the way for decisions regarding marketing activities to be made in an automated manner. In this way, the effectiveness of marketing activities has increased by establishing relationships with consumers in the right way at the right time. Especially when it is considered that 76% of consumers expect businesses to understand them, the importance of the contributions that AI will bring to marketing activities can be easily understood [32].

Developments in communication and information technology and the use of AI have positive effects on the analysis and processing of biometric data [4]. Biometric data is especially important for decision-makers in the planning of personalized marketing activities [12]. Biometric identifiers are classified as physiological and behavioral characteristics [18]. Human gait is a behavioral identifier and by using it as a cue, it is possible to overcome the limitations of physiological identifiers. For example, capturing a fingerprint requires cooperation of the subject. However, capturing human gait is achievable from larger distances and at low resolution which makes the utilization of this trait desirable. Furthermore, these benefits of using gait as biometric identifier enable to analyze human attributes in the wild [40].

Human gait differs among age groups and several studies corroborate this argument. Grabiner, Biswas, and Gabiner [11] proved that age affects the stride width. Correspondingly, Elble et al. [9] showed that as the age increases, the walking speed and stride decreases. Thus, the arm swinging, rotation of joints and the maximum amount of foot height changes. These findings indicate that as the age differs, so does the gait patterns and therefore it is achievable to deduce age based on human gait.

It is possible to leverage gait-based age estimation in different systems. For instance, a system that is set up on a street may estimate age of pedestrians, which then can be used to display targeted advertisement on electronic billboards. Another probable use case can be shown in criminal investigation field. In the case suspect's face is not visible, estimating the age may provide important information to the law enforcement. These cases exhibit that gait-based age estimation can provide valuable information.

There have been various studies to infer age based on gait. While studies such as [2, 5, 7, 8, 27, 29, 44, 47] aim classifying subjects into their age group, other studies [1, 14, 21-25, 26, 28, 35, 37, 38 ,42, 43, 45, 46, 48] aim estimating the age of the subjects. Although these studies approach the problem in different ways, the general frame is usually the same which consists of processing subject's gait footage, feature extraction and classification/estimation.

There are two concepts of the processing step which are model-based and model-free [33]. Model-based approaches target creating models from locomotion of body parts and model-free approaches focus on spatiotemporal pattern of human gait, generally by forming representations from binary silhouettes. Even though both concepts have their advantages and disadvantages, the ability to apply model-free approaches in real-time environments due to their efficient nature has made them more appealing. Gait Energy Image (GEI) is among the most utilized representations in model-free approaches [20]. It is constructed by converting gait footage into binary gait silhouettes, pinning the frames that are in one gait cycle and averaging these frames. By doing so, a representation that can describe the subject's both locomotion and posture are obtained. Thus, this makes GEI an important gait feature descriptor. However, it is important to note that the performance of the methods that rely on GEI are susceptible to the conditions such as clothing and object carrying in the original footage [36].

The next steps are feature extraction and interpreting these features to reach a conclusion. To fulfill these steps, the usability and the effectiveness of various learning methods were researched by previous studies. Additionally, the choice of dataset is crucial in deep learning-based methods and the dataset needs to be balanced and extensive in order to obtain unimpaired results.

A CNN, which is a hierarchical multilayered neural network, can extract features and do the learning directly from the image. Recent studies have been giving a great deal of attention to CNN due its success on tackling harder problems. In our study, the feasibility of different CNN models which retrieve GEI as an input for gait-based age estimation is explored with the aim of low mean absolute error (MAE) and median absolute error (MedAE). While doing so, several different state-of-the-art deep learning models such as EfficientNetB7, RegnetY, CrossVIT, InceptionV3 and ResNet152 were tested, and their performances were evaluated. Thus, this study provides guidance on applying networks for the gait-based age estimation, a critical biometric identifier for marketing activities. Beyond its implications for marketing, the methodological framework presented here is relevant to a wide range of computing applications, including intelligent surveillance systems, adaptive human–computer interaction, and privacy-preserving demographic analytics.

The rest of the paper is organized as follows. Section 2 elaborates on how AI technologies are transforming marketing strategies and practices. Section 3 presents the gait dataset that was used for the experiments. Section 4 summarizes the configurations of the CNN architectures used. Section 5 contains the performance metrics, experimental results, and comparisons with previously published methods. Finally, section 6 concludes this study along with the future research directions.

2. Artificial Intelligence in Marketing

In recent years, one of the most important issues in marketing activities is to establish and maintain healthy relationships between businesses and customers. These established relationships ensure that consumers' expectations can better be understood and products that meet consumers' needs and wants can be produced. Collecting and using data related to their needs and wants at the right place and time is very important for the success of marketing activities. The data used in the planning of marketing activities can be obtained from marketing research, market analysis and competition intelligence. In addition to this, today developing technologies and communication tools have made it easier to access various data about consumers [17]. This makes it easier to predict what the consumer wants and needs [15].

AI emerges as a crucial partner in marketing, which supports the automation, optimization, and augmenting of three critical marketing processes: gathering data, generating insights through analysis, and engaging with customers [17]. Thanks to the use of consumer data and customer profiles by AI tools, healthier communication can be established with the target audience and communication can be established by creating tailored messages for each consumer [32]. This is related to AI that have the ability to recognize faces and things. Thanks to AI technology, businesses can make some recommendations to the consumers about the most suitable products that will meet their demands and needs [16]. In short, analysis of large volumes of data have become easier with AI. Besides, it enables valuable information to be delivered to consumers. Visitor activity is monitored to quickly display personalized ad content. Data is continuously gathered and used to inform future changes in advertising materials. It facilitates easy customer support. For marketing automation, AI applications in marketing play an important role. Furthermore, it enables data to be processed at a level close to zero error and in a short time. Customer centered choices can be made with the ability of AI to scan many different data points such as blogs and social media [13]. Thus, it is ensured that the automated marketing campaigns organized by the businesses reach the right customers [16]. AI provides cost savings in businesses as well. Various activities that are carried out by humans with intensive work can be carried out in less time and at low costs with the integration of AI into marketing activities. In other words, the way to make fast and effective decisions in businesses is through AI [32]. Apart from these, in the customer segmentation algorithms for clustering, such as k-means and hierarchical clustering, can successfully group customers based on their demographic information, purchasing history, and online browsing patterns [31]. Thus, customer segmentation activities can be carried out more effectively.

3. Data Set

This work utilized the OU-ISIR Gait Database, Large Population Dataset with Age (OULP-Age) [41]. It contains GEI of 63,846 subjects and the footage of these subjects are recorded in front of a green screen thus the GEI construction scheme is free from the external factors. An example of the constructed GEI can be seen in Fig. 1.

Fig. 1 An example of GEI in OULP-AGE

The subjects are aged between 2 and 90 years old. This tells that the dataset comprises of an entire generation. Moreover, even though most of the subjects are between ages 6 and 50, the dataset is able to depict alterations that occur between different age groups (Figure 2).

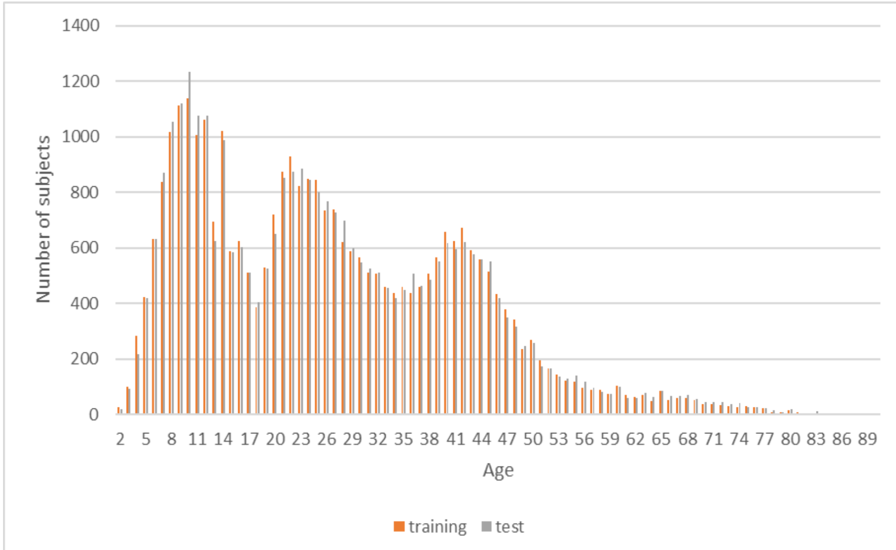

Fig. 2 Age distribution of the OULP-Age Dataset

The human gait is affected by the gender therefore the gender distribution may affect the age estimation and there is a correlation between age and gender in terms of gait [25]. The dataset consists of 31,093 males and 32,753 females therefore the dataset is balanced in terms of gender.

The OULP-Age dataset is suitable for this work because a) the dataset is balanced in terms of age and gender which is important because the ratio of the classes can affect the outcome of machine learning approaches, b) the dataset is the largest one currently available which is one the keys to success in deep learning approaches and c) the dataset consists of GEI which is composed in an environment that aids minimizing the errors that could occur during GEI construction.

4. Methods and Evaluation

In this study, to estimate gait-based age, five CNN architectures were selected: EfficientNetB7, RegNetY, CrossVIT, InceptionV3 and ResNet152. These CNN architectures were selected due to the nature of the input data, which are 2D spatial summaries of the temporal gait cycles. These image-based representations are more effectively processed using CNNs, which are optimized for extracting spatial hierarchies and visual patterns.

EfficientNetB7 uses a compound scaling approach to optimize accuracy and efficiency. This model systematically scales the depth, width, and resolution of the network, thus excelling in image classification tasks while maintaining low computational costs [39].

RegNetY was developed for using a design space that automatically determines the optimal model configurations. RegNetY focuses on efficient block design with channel scaling and bottleneck blocks, which ensures high accuracy and low computational costs in large-scale image recognition tasks [3].

CrossVIT represents a variant of the Vision Transformer (VIT) model. It is designed to learn both local and global features using multiple imaging windows at different scales. The parallel operation of image processors of different sizes enables CrossVIT to perform effectively in complex image analysis tasks. Moreover, its ability to process complex data structures makes it particularly advantageous in various applications [6].

InceptionV3 was developed with the aim of improving the efficiency of deep learning models. It uses a parallel combination of filters of different sizes to achieve high accuracy and minimize computational cost. It is a widely used model for tasks such as image classification and object detection [34].

ResNet152 improves the trainability of ultra-deep networks by including residual blocks. This network, consisting of 152 layers, addresses the gradient loss problem through bypass connections, thereby improving the accuracy of deep models. It is frequently chosen for tasks such as large-scale image classification and feature extraction [19].

These architectures were designed for classification purposes. To perform regression for age estimation, the last fully connected layers of these architectures were altered to have one unit with linear function.

We used a 5-fold cross-validation approach to evaluate model performance. The dataset was randomly partitioned into five equal subsets, ensuring an even distribution of age and gender across folds. Each model was trained on four folds and validated on the remaining fold, repeated five times to compute the average performance. To prevent data leakage, care was taken to ensure that no GEI samples from the same individual appeared in both training and validation sets. Additionally, the models were trained using a learning rate of 0.01 for 30 epochs.

To evaluate the performance of the models used for age estimation in the relevant study, evaluation metrics such as Correlation Coefficient, Determination Coefficient, Median Absolute Error, Mean Absolute Error and Root Mean Square Error were used [10].

The Correlation Coefficient (R) is one of the measures that help to determine how closely related the actual values and the values predicted by the model are. It takes on a value between -1 and 1 where 1 and -1 show perfect correlation in a linear regression while 0 shows no linear correlation. A perfect positive linear relationship has a value of +1 while a perfect negative linear relationship has a value of -1. This means that a value of zero indicates that there is no linear relationship between the two variables in question.

The Determination Coefficient (R2) shows the proportion of variance in the dependent variable that is explained by the independent variables. It takes on values between 0 and 1 where a value of 1 show that the model can accurately predict the dependent variable. R^2 statistic shows the how closely the model's predicted values are to the actual observed values.

The Root Mean Square Error (RMSE) is calculated by first squaring each of the residuals and then computing the square root of the average value of these squared residuals Eq. 1). RMSE pays more attention to the size of the errors and is also quite sensitive to large errors as well. Hence, it is used when precision is an important factor in assessing the performance of the model.

$$RMSE = \sqrt{1/n \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \qquad (1)$$

The Median Absolute Error (MedAE) indicates the middle of the absolute differences between the estimated and real targets (Eq. 2). Thus, MedAE is a more stable error measure as it is not influenced greatly by outliers and is used to minimize the influence of these on the data set.

$$MedAE = Median(|y_i - \hat{y}_i|) \qquad (2)$$

The Mean Absolute Error (MAE) represents the mean of the absolute differences between the predicted and actual values (Eq. 3). Unlike metrics that square the differences, such as the RMSE, MAE assigns equal weight to all individual errors, providing a straightforward and interpretable measure of the model's predictive.

$$MAE = 1/n \sum_{i=1}^{n} |y_i - \hat{y}_i| \qquad (3)$$

5. Results and Discussion

Table 1 illustrates the age estimation regression performance of the employed models. Accordingly, the CrossVIT model demonstrates superior performance in all metrics and reached the values of 0.9505, 0.9034, 1.4758, 2.6854, 4.8135 for R, R2, MedAE, MAE, RMSE metrics, respectively. Although EfficientNetB7, RegNetY models fall behind the performance of the CrossVIT model, they have reached promising performances. While the performance achieved for the EfficientNetB7 model is 0.9319, 0.8685, 1.9122, 3.3912, 5.6156 for the same evaluation metrics, respectively; these values are measured as 0.9301, 0.8651, 2.0398, 3.5632, 5.6877 for the RegNetY model. While the InceptionV3 model exhibited superior performance to the ResNet152 model, these two models demonstrated the lowest performance.

Table 1 The experimental results

	R	R2	MedAE	MAE	RMSE
EfficientNetB7	0.9319	0.8685	1.9122	3.3912	5.6156
RegnetY	0.9301	0.8651	2.0398	3.5632	5.6877
CrossVIT	**0.9505**	**0.9034**	**1.4758**	**2.6854**	**4.8135**
Inception V3	0.9058	0.8205	2.0082	4.0187	6.5608
ResNet152	0.8751	0.7657	2.5940	4.7318	7.4951

The variations in the performance of the models can be explained by architectural complexity, feature representation, and learning ability. For instance, CrossVIT can learn dependencies better with the help of VIT based approaches. This makes it easier for the model to capture relationships in regression tasks and this way low errors can be realized. Other models like EfficientNetB7 and RegNetY are the modern CNN architectures which have been developed with a focus on parameter and computational efficiency. These models have a well-balanced performance in terms of the accuracy and the errors as well. Although ResNet152 has a very complex network architecture, too many layers may cause a problem known as 'gradient fading' thus decreasing the performance of the network. CrossVIT can make more general and accurate predictions as it has the capacity to learn the local and the global features at the same time. This enhances the R-score and minimizes the errors. InceptionV3 employs multi-scale filters for feature extraction. But this approach may not be able to identify some complex features at times, which may result in relatively higher error rates. RegNetY possesses a flexible modular architecture in feature extraction. Such choice of the layer width and the number of channels ensures that the model learns features in the most efficient manner. This makes the ResNet152 capable of extracting high-level features given that there are numerous layers but may compromise on the generality of features in some cases.

The comparison of the result obtained with CrossVIT and the existing studies in the literature are shown in Table 2.

Table 2 Comparison of the gait based age estimation methods

Method	**MAE**
[45]	6.27
[37]	5.84
[38]	5.79
[48]	5.12
[1]	3.70
[42]	5.43
[43]	8.39
CrossVIT (Our result)	**2.69**

The results of the compared methods were obtained by training on OULP-Age dataset and all these methods utilize a deep learning approach. The CrossVIT method in this study outperforms the method proposed in [38] which utilizes gender and age group information that is extracted before the age estimation. Furthermore, CrossVIT has also achieved much better results than the network that is proposed in [37] which is based on DenseNet. Similarly, the CrossVIT method outperforms GL-CNN that was proposed in study [48] in terms of MAE. GL-CNN is composed of multiple CNN architectures to extract information from both local parts of the GEI and the GEI as whole. Moreover, although an age and gender-based approach proposed by Abirami et al. [1] achieved the closest performance to CrossVIT, it fell short of the CrossVIT model. Finally, CrossVIT model outperforms the two more recent studies conducted by Xu et al. [43] and Xu et al. [42]. The former one is based on an uncertainty-aware gait-based approach, while the latter includes a real-time CNN framework from a single image. Like CrossVIT, other two approaches, EfficientNetB7 and RegNetY presented in the study, have achieved more successful results than the current literature.

These results illustrate the effectiveness of combining transformer-based and convolutional approaches for structured visual data, highlighting a pathway for the development of next-generation hybrid architectures, which is an area of significant interest in contemporary computing research.

6. Conclusion and Future Work

The developments in technology have made significant contributions to the businesses' ability to continue their existence in a competitive environment. The dizzying speed of technology has significantly affected the marketing activities of the companies. Technology has opened the doors for marketing managers to access the data they need faster and more efficiently.

Considering the fierce competitive environment, it would not be wrong to say that data is an important key for businesses to achieve successful activities. Decision makers in marketing are constantly flooded with large volumes of data. At this point, artificial intelligence aids them by leveraging predictive analytics by efficiently gathering and interpreting these data. Besides, the use of AI in marketing has paved the way for personalization.

This study explored the use of various CNN architectures for gait-based age estimation using Gait Energy Images (GEIs), with CrossVIT emerging as the most effective model across multiple evaluation metrics. The proposed approach not only achieves state-of-the-art performance but also highlights the potential of leveraging behavioral biometrics in data-driven decision-making. The best performing CrossVIT model is a variation of the VIT model designed to capture both fine-grained (local) movements such as joint rotations and broader (global) gait patterns like stride length by utilizing image windows of different scales. Its parallel processing of varied window sizes allows it to model complex age-related characteristics more effectively than traditional CNNs. This hybrid attention mechanism enhances its sensitivity to nuanced motion cues that correlate with age. The second-best solution, EfficientNetB7 employs a compound scaling method to enhance both accuracy and efficiency by proportionally adjusting the network's depth, width, and resolution. This enables it to achieve high performance in image classification tasks while keeping computational costs low. The third-best solution, RegNetY is designed with an automated approach to identify optimal model configurations. It emphasizes efficient block design using channel scaling and bottleneck blocks, achieving high accuracy and low computational costs for large-scale image recognition tasks.

Beyond technical contributions, this research has practical implications for marketing practices. Accurate age estimation through non-intrusive gait analysis enables businesses to deliver personalized content in public environments—such as targeted advertisements on digital billboards—or tailor in-store experiences based on customer demographics. These capabilities contribute to more effective consumer segmentation, real-time profiling, and data-informed campaign strategies, all while preserving user anonymity. From a computing perspective, the proposed approach exemplifies how advances in deep neural architectures can be translated into practical, scalable solutions that bridge research and application.

Despite promising results, several limitations must be acknowledged. First, although the OULP-Age dataset provides high-quality GEI images with minimal background noise, it does not include labeled metadata for walking speed or clothing conditions. Therefore, the model's robustness across such variations could not be assessed in this study. Future work will involve evaluating the models on more diverse datasets (e.g., CASIA-B or TUM-GAID), which include covariates such as carrying conditions, walking speeds, and clothing changes. Additionally, while the OULP-Age dataset is extensive and balanced, any model trained on a specific demographic distribution may exhibit biases when applied across different cultures, postures, or age ranges. Finally, the model's interpretability, though addressed using quantitative metrics, could benefit from further exploration through visual explanations or explainable AI techniques.

Future research could address these limitations by incorporating multimodal data (e.g., gait + facial cues or skeletal tracking), testing on in-the-wild datasets, and refining interpretability using saliency maps or attention visualizations. Further, utilizing more advanced transformer-based architectures or hybrid models that combine CNNs and vision transformers may refine the ability to capture local and global features. With these improvements businesses will likely continue to experience significant impacts from emerging technological advancements. Artificial intelligence, as one of the most prominent technological developments, will play a pivotal role in this transformation.

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