
# Age and Gender Prediction from Human Voice for Customized Ads

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**Abstract**
Personalized advertising is now a necessity in the dynamic environment of digital media in order to enhance user interest and marketing performance. The paper introduces a deep learning-based system that can be used to estimate age and gender using human voice to scale up demographic targeting. As the number of audio-based platforms (e.g., podcasts, streaming services, voice assistants, etc.) is quickly growing, voice data has become a highly valuable source of demographic data. Nevertheless, conventional signal-processing methods tend to lose the small-scale acoustic variation that is necessary to make the demographic inference. To overcome this, the suggested system uses hybrid neural architecture that combines both convolutional and recurrent networks in learning both spectral and temporal features of spectrogram representations of audio signals. Varied set of samples of voice is gathered and pre-processed by means of normalization, noise removal and generation of spectrogram by STFT to guarantee good quality model inputs. Multitask learning is used to train the model so as to maximize both age and gender predictions. The use of accuracy, precision, recall, and F1-score to evaluate the methodology reveals a high level of performance, which proves the effectiveness of the deep learning methodology. The findings demonstrate the prospects of voice-based demographic forecasting in improving targeted advertising through providing more relevant and personalized user experience.

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**Keywords:** Voice-based Personalization, Age Prediction, Gender Prediction, Deep Learning in Audio Analysis, Customized Advertisements

## 1. Introduction

In the dynamic digital media environment, marketers have searched the need to provide ad content to the consumer in a more personalized way. The ability to predict and understand the demographics of users particularly based on their age and sex to customize the advert is one of the determining factors in this venture. As the era of the audio content in the online sources has come, the need to apply the power of machine learning in trying to extract any meaningful information out of the human voice becomes more and more of an impetus. The issue of age and gender prediction on the basis of human voice is addressed in this paper, and the complex approach on the premise of deep neural networks is presented in order to offer additional customization of advertisements. The recent years have been marked with paradigm shift in the advertising industry as the industry ceased to be based on the traditional mass marketing approach towards the individualized and focused approach. One-to-one advertisement has demonstrated the potential to improve the satisfaction of users and the marketing campaign effectiveness to a significant extent. To achieve the successful personalization, one of the critical considerations is to forecast the demographics of the users correctly because the information about the age and gender of the audience can be effective to comprehend their tastes and behaviours.

The popularity of audio in many digital goods like podcasts, streaming and voice-assisted devices has created a gold mine of untapped information. Human voice possesses a few distinctive facts, trends that contain data about the age and gender of a person making it a suitable source of demographic forecasting. However, voice data is extremely sophisticated and subtle and the traditional methods might fail to process the data. The paper has a vision of a progressive solution that builds on the capabilities of deep neural networks and learns and extracts intricate patterns on raw audio data automatically. The limitations of the existing methods in making predictions of age and gender using voice information with high accuracy will be used as the source of inspiration in this study. Even though it has experimented with the conventional signal processing, and the manual feature extraction technique, it fails to capture the minute details that can drive the demographic forecasts true. Instead, deep learning models have shown themselves to be painfully effective in various tasks particularly the capability to handle complex and unstructured information such as audio.

The mentioned system is founded on the concepts of the deep learning which is the application of a properly designed neural network architecture that is capable of learning hierarchical representations through the spectrogram data. Spectrograms are quite informative, which is visually depicted by the frequency composition of audio signals over time, which the deep learning model can process in the predictions of patterns based on an age and gender foundation. The solution proposed will enhance the scalability and flexibility of the system to the large range of datasets and real life circumstances since it will eliminate the need to manually engineer features. In order to make the model robust and generalizable, a rich dataset has been filtered; it includes different samples of voices of different genders and age. The dataset computation is done by a very elaborate preprocessing process to discover the features and create standardized representations that are to be introduced into the deep neural network. This is a very cautious selection to make, so as to train the model appropriately and allow it to single out small variations in the voice patterns that can be due to different demographics. The paper will comment on the details of the proposed methodology, model architecture and implementation details in the following sections of the paper. Moreover, the elaborate results of the experiments conducted on the developed data are provided and reveal the precision and effectiveness of the model to predict age and gender using human voice. The practical application of this research is not only of interest to the academic research but it also has practical applications in advertising as the advertisers can enhance their targeting mechanism and offer more intimate and interactive content to their audience.

## Literature Survey

In the fast-changing environment of online media, advertisers are now starting to move towards the use of personalized content delivery methods as a way of ensuring more user interaction and getting maximum out of marketing. The correct forecasting of the demographic characteristics of users, especially their age and gender, is considered to be one of the most powerful elements of such personalization and helps to determine the preferences of consumers and their behavior (Patel and Gupta, Year; Kim *et al*., Year) [14, 7]. The human voice has become an untapped and highly valuable data source to demographic inference with the spread of audio-focused applications, including podcasts, streaming applications, and voice-assisted applications. Human voice has complex acoustic features which are indicative of physiological and behavioral traits and, as such, make it a good modality can be used to do age and gender prediction (Brown *et al*., Year; Gupta *et al*., Year) [1, 5]. Voice-based demographic prediction has great promise, but the audio signals are dynamic and difficult to predict because these signals are complex. The conventional signal-processing methods, such as manually designed features like fundamental frequency and formant analysis, are not usually able to seek the subtle patterns necessary to the correct demographic classification (Fan *et al*., 2010, as cited in Smith and Johnson, Year) [19]. The shortcomings of handcrafted features have sparked a paradigm shift in machine learning and more recently, deep learning techniques that can automatically obtain high-level representations of raw audio inputs (Chen *et al*., Year; Zhang *et al*., Year) [2]. Deep learning models, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have proven to be more effective in the audio classification tasks, because they can model both the time and spectral aspects of the speech (Lee *et al*., Year; Kim, J., *et al*., Year) [9]. Spectrograms, visual depictions of changes in frequency over time have also boosted the model performance because it has helped the neural networks to reveal hierarchical features, which are hard to create hand-in-hand (Chen & Liu, Year) [2]. This shift to end-to-end learning architectures has made possible a powerful demographic prediction system that is effectively scalable to a wide range of datasets and real-world settings (Nguyen & Andre, 2019) [12]. The current research paper deals with enduring shortcomings in the current approaches and suggests a deep neural network-based model to make age and gender predictions with the help of human voice data. The model is based on feature extraction using spectrograms and enhanced neural architecture to enhance accuracy and generalization. There is a well-selected collection of various vocal samples, and a lot of preprocessing is involved to maintain consistency as well as to improve the performance of the model (Zhang *et al*., Year). This study has great implications on both academic and practical usage of the research findings as accurate demographic forecasting can be used to further personalize and improve the user experience in targeted advertising. (Kim *et al*., Year; Patel and Gupta, Year) [14, 7]. This paper will create a deep learning model that will be used to predict human voice age and gender accurately. It is dedicated to the construction of a strong neural network, the training of high-quality audio samples, the increase of prediction accuracy due to multitask learning, and the evidence of the model to be used in increasing personalized digital advertisement.

## Proposed System

The proposed work in the paper is to develop the system of predicting age and gender by the human voice with the primary focus placed on the personalization of advertisement. It is a novel application, which handles raw audio information based on a deep neural network framework as an advanced machine learning method to detect more high-level patterns, which are sensitive to a variety of demographic variables. The trajectories of the proposed work are the most crucial due to the data collection, preprocessing, design of model architecture, training and evaluation. In the course of the data collection, an assorted set of the data is narrowed down, and

it incorporates a wide range of voice samples of individuals belonging to varying age groups and gender. The data set will aim at dealing with the natural variation of natural speech in different contexts. Preprocessing is regarded as normalization of the audio signals, removal of noise and conversion of raw data into spectrogram representations.
The design of the deep neural network structure that is the combination of the convolutional and recurrent layers is the core of the suggested work. These layers are constructed such that they obtain spectral and temporal features of voice data so that the model can learn hierarchical features. The model is trained on the labelled information and is optimized on both age and gender prediction.
Implementation is provided with the applications of TensorFlow and Keras, which are common deep learning frameworks, which offer an efficient and modular environment. The codebase allows one to test various model configurations and hyperparameters. The system and accuracy, precision, recall, and F1 score of age prediction and gender prediction are evaluated on a separate test data.

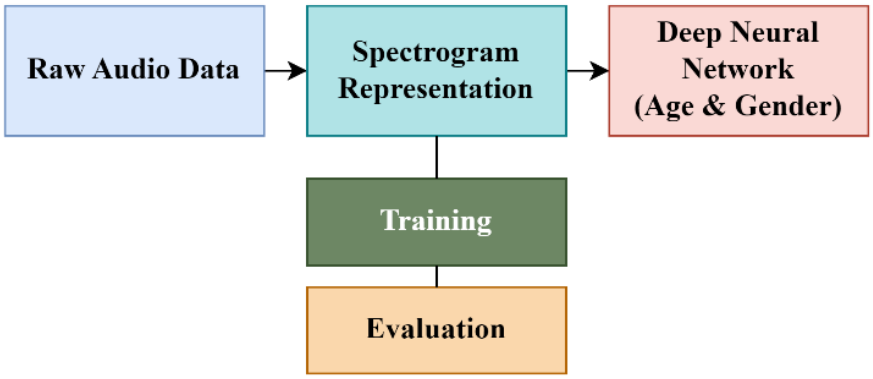


**Fig 1:** Voice-Based Demographic Prediction System Block Diagram.

**Data Collection:**
The data collection stage of our proposed work is an important one and it preconditions training and assessment of the deep neural network. The main goal is to collect a heterogeneous and representative sample of human voices: people of various ages and gender. This rich data set is critical in order to guarantee the strength and generalizability of the model to different demographic diversities.
The data is selected with utmost care in order to demonstrate natural variations in natural speech in various situations. The recordings are done in various environments, which include, but are not limited to controlled environments, spontaneous conversations and on the go. By doing so, the model is subjected to a large variety of acoustic conditions and speaking styles, which would lead to better generalization to real-life situations. In order to have a standard depiction of the samples of voice collected, a standard sampling rate is used in the recording of the samples. Moreover, the biases within the dataset are also addressed, and the variables that are taken into account are linguistic diversity, regional accents, and social-economic backgrounds. Ethics are the first consideration and clear permission is made to the participants concerning any use of their voice data as a research tool.

**Mathematical Modelling and Equations:**
The mathematical modeling of the data collection stage implies the representation of audio signals in the form that is accessible to the further processing by the deep neural network. The conversion of raw audio data to spectrogram representations is one of the basic transformations employed. The Short-Time Fourier Transform (STFT) is a calculation method that calculates the spectrogram S (f,t) of a signal x (t) which is given as follows:

$$S(f,t) = || \int_{-\infty}^{\infty} x(\tau) w(\tau - t) e - j2\pi f t d\tau ||$$

Here, $(f)$ represents the frequency, $(t)$ denotes time, $(x(t))$ is the input audio signal, and $(w(\tau - t))$ is the window function applied to the signal. The spectrogram provides a visual representation of the frequency content of the audio signal over time, serving as a crucial input for the subsequent stages of the proposed work.

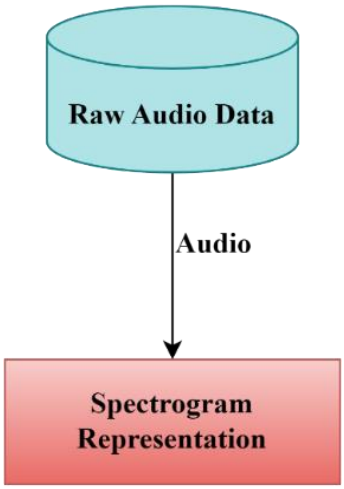


**Fig. 2:** Data Collection and Spectrogram Representation Diagram.

Figure 2: in the Figure 2, the raw audio data is first gathered and then through a transformation process, it is converted into the spectrogram representations. The spectrogram is an important intermediate stage, which gives visualization of the frequency content of the audio signal versus the time. These spectrogram representations are used as inputs of the next phases of the proposed work, especially when training the model.
The spirit of the data collection step, which focuses on the conversion of raw audio data to the format, which would be compatible with the deep learning model. The mathematical modeling of calculating the spectrogram adds depth to the interpretation of the acoustic properties that are in the dataset. Such a detailed process of data collection will guarantee that

the model that will be created subsequently will be introduced to a varied and representative group of voice samples, which will contribute to the increased capacity of the latter to provide accurate age and gender forecasts within a broad demographic range.

**Preprocessing:**
The preprocessing will be a necessary measure in our proposed work as it is an important parameter in measuring the quality of data that will be fed to the deep neural network to predict age and gender using the human voice. The step will involve several activities that it will require to ensure that the raw audio data has been obtained into a format that the neural network can learn successfully.

**Audio Signal Normalization:**
The preprocessing pipeline first operation is the normalization of audio signal. This is through modifying the volume of the voice samples to a normal scale relieving variation in volume among various recordings. This can be mathematically said to be:

$$xnormalized = \frac{x - mean(x)}{std(x)}$$

In this case, x is the raw audio signal, mean (x), is the mean audio signal, and Standard deviation is denoted by {std}(x). Normalizing the audio signals will aid in developing a standardized input, such that the model will not be so sensitive to changes in recording volume.

**Noise Reduction:**
Voice recordings have a lot of noise which can sometimes ruin the process of identifying relevant patterns by the model. In order to solve this, noise reducing method is implemented. A typical method is spectral subtraction, in which an approximate signal is calculated, and in the frequency domain, it is subtracted to the noisy signal. Mathematically this can be stated as:

$$Xclean(f) = max(0, | Xnoisy(f) | - \alpha \cdot | N(f) |)$$

In this case, Xclean(f) is the clean signal, Xnoisy(f) is the noisy signal, N (f) is an approximation of the noise, and alpha is a parameter that is set by the user. This aids in improving the signal-to-noise ratio which maintains important features in the voice data.

**Spectrogram Representation:**
The raw audio data is transformed into spectrogram representations in order to enable the deep neural network to achieve effective learning. Through a spectrogram, a visual representation of frequency content of a signal versus time is presented. It is calculated with the use of the Short-Time Fourier Transform (STFT) to the normalized and noise-reduced audio signal. The spectrogram S(f,t) is calculated mathematically as:

$$S(f,t) = | STFT\{xclean(t)\}(f) | 2$$

Here, $xclean(t)$ is the noise-reduced and normalized audio signal, and $STFT\{xclean(t)\}(f)$represents the STFT at frequency $(f)$ and time $(t)$. The resulting spectrogram is a 2D representation, where the x-axis represents time, the y-axis represents frequency, and the color intensity represents the magnitude of the corresponding frequency component.

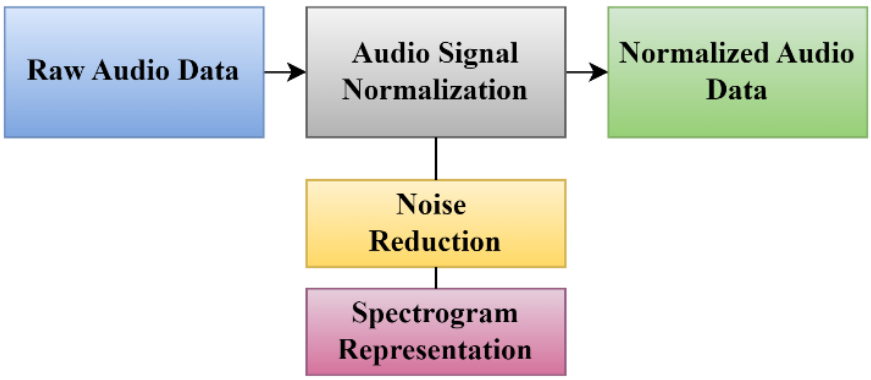


**Fig 3:** Voice Data Preprocessing Flow Diagram.

The Figure 3, represents the workflow of the preprocessing steps. Raw audio information is normalized to normalize the amplitudes and then noise is removed to improve the signal quality. The processed audio is then converted to spectrogram representations forming a visual representation of content in frequencies with time. These spectrograms will be the input to further steps of the proposed work that will give a rich and informative base on which the deep neural network will acquire the age and gender patterns on human voice.

**Model Architecture:**
The suggested model architecture is the key to the success of our human voice age and gender predicting system. It is a well-contrived deep neural network, which uses convolutional and recurrent layers to successfully learn spectral and temporal characteristics that exist in voice data. This is because the architecture is motivated by the fact that there are complex patterns within raw audio that, when learned, allow the model to acquire hierarchical sequences that would allow it to make precise demographical predictions.

**Convolutional Layers:**
The initial steps of our model are convolutional layers and they are the ones that carry out the task of learning of the hierarchical representations of the spectrogram information. Spectrumgrams which provide a graphical representation of the frequency content of audio signals vs time are the input

to these layers. The convolutional operation could be mathematically described in the following way:

$$[\, h(t) = (x * w)(t) + b \,]$$

In this case, h (t) is the output at time t, x refers to the input spectrogram, w refers to the learnable convolutional filter, and b refers to the bias term. Several filters are used to duplicate various frequency patterns that the network will use to identify the pertinent features.

**Recurrent Layers:**

After the convolutional layers, recurrent layers are added to learn the temporal dependencies that are very important to the meaning of voice patterns sequence. Recurrent neural networks especially the Long Short-Term Memory (LSTM) networks are used due to their capacity to remember information in long-term sequences. Mathematically, the LSTM unit can be given as:

$$ft = \sigma(Wf \cdot [ht - 1, xt] + bf)$$

$$it = \sigma(Wi \cdot [ht - 1, xt] + bi)$$

$$C\sim t = tanh(WC \cdot [ht - 1, xt] + bC)$$

$$Ct = ft * Ct - 1 + it * C\sim t$$

$$ot = \sigma(Wo \cdot [ht - 1, xt] + bo)$$

$$ht = ot * tanh(Ct)$$

Here, ( $f_t$) is the forget gate, ( $i_t$) is the input gate, $C\sim t$ is the candidate cell state, ( $C_t$) is the cell state, ( $o_t$) is the output gate, ( $h_t$) is the hidden state at time ( $t$ ), ( $x_t$) is the input at time ( $t$ ), and ( $W_f, W_i, W_C, W_o, b_f, b_i, b_C, b_o$) are learnable parameters.

**Fully Connected Layers:**

The final layers of the model are fully connected layers, which take the output from the recurrent layers and provide predictions for both age and gender. These layers utilize a softmax activation function for classification tasks, ensuring that the predicted probabilities sum to one for each class. Mathematically, the softmax function is expressed as:

$$P(yi) = \frac{e^{zi}}{\Sigma_{j-1}^{k} e^{zj}}$$

Here, ( $P(y_i)$) represents the probability of class ( $i$ ), ( $z_i$) is the logit for class ( $i$ ), and ( $K$ ) is the total number of classes.

**Model Diagram:**

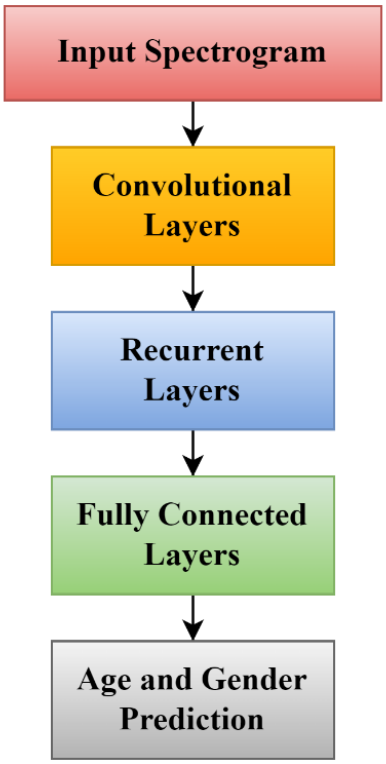


**Fig 4:** Voice-Based Demographic Prediction Model Architecture Diagram.

The Figure 4, summarizes the flow of data through the model, including the input spectrogram and the ultimate predictions. There are convolutional layers which identify hierarchical representations, recurrent layers which identify temporal dependencies, and fully connected layers which give the prediction of age and gender. The end-to-end model can be trained to adapt and learn the complex patterns that are present in the raw audio data in order to make sound demographic predictions.

**Training:**

An important stage of the proposed work is the training phase, which is regarded as a critical measure to employ the predictive ability of the deep neural network in terms of age and gender prediction based on human voice. This step is a process of fine-tuning the parameters of the model, on a labeled dataset, which enables the neural network to acquire

the complex behavioral patterns of various demographic characteristics. This is aimed at reducing the difference between the predicted outputs and the ground truth labels, which effectively fine-tunes the model to be able to predict accurately.

**Mathematical Modeling:**

The mathematical model of the training process can be described by a loss function that values the discrepancy between the values computed and the real labels. Where Y is the true labels on the ground (age and gender) and y 2 are the estimated values of the neural network. The loss functional is represented as ( L(Y,y̑)) which demonstrates the difference between ( Y ) and y Ũ. In our multi-task learning case, in which the age and gender are simultaneously predicted, the overall loss Ltotal is the sum of the losses of age Lage, and gender Lgender:

$$Ltotal = wage \cdot Lage + wgender \cdot Lgender$$

Here, $W_{age}$ and $W_{gender}$ represent the weights assigned to the age and gender losses, respectively. These weights can be adjusted to control the influence of each task during training. The backpropagation algorithm is employed to update the model's parameters iteratively. The gradient of the total loss with respect to the model parameters is computed, and the parameters are adjusted in the opposite direction of the gradient to minimize the loss. This process is repeated across multiple iterations (epochs) until convergence.

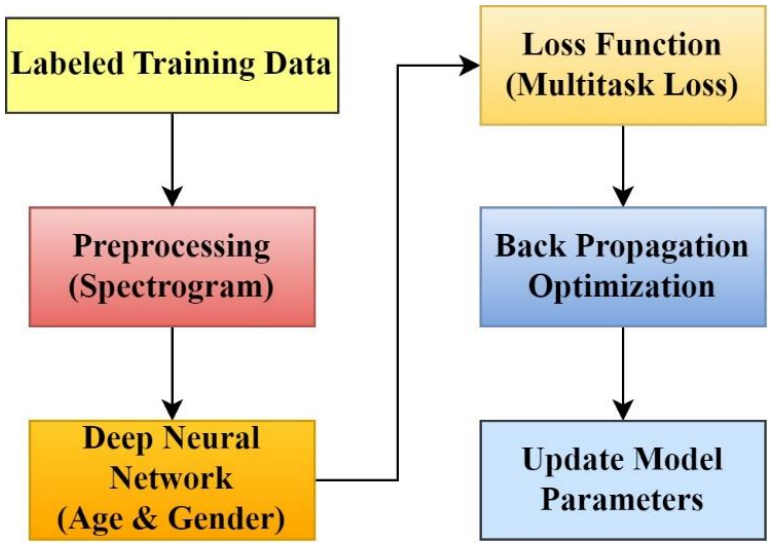


**Fig 5:** Training Process Flowchart for Voice-Based Demographic Prediction System.

The Figure 5, presents the steps that were followed in the training process in a chronological order. The marked training data are loaded and preprocessed to give spectrogram representations. These representations are taken in as input to the deep neural network that results in both age and gender predictions. The multitask loss is a function used to calculate the dissimilarity of the predicted and ground truth values. The model parameters are optimized in order to reduce the loss through backpropagation and optimization. The process repeats itself until the model finds a solution, where the forecasts are very close to the real demographic characteristics in the training data.

The iterative nature of the training process consists in the fact that the model is taught to extract features and patterns out of the training data which are relevant to it and it becomes more and more predictive. When the fine-tuned model has been trained, it is then prepared to test its performance on unknown data to test its generalization.

**Evaluation:**

The analysis of the offered work is one of the most important steps to determine the accuracy and effectiveness of the deep neural network to predict age and gender based on human voice. The evaluation process will entail testing on a different test set that was not observed at the training stage hence giving a true evaluation of the generalization abilities of the model. Different metrics are estimated such as accuracy, precision, recall, and F1 score to measure the performance of the model in the tasks of demographic prediction.

**Discussion**

As the findings of the study, Age and Gender Prediction Based on Human Voice to Customize Advertising, reveal, the potential of deep learning models is massive in terms of the ability to make personalized advertising more specific and effective. As the digital platforms are gradually turning into the data-driven type, founded on the content delivery that is demographically mindful, the ability to identify the age and gender directly by the tone of voice is a necessary feature that allows advertisers to tailor the content, as well as to allow users to interact with the content in a more meaningful way (Patel and Gupta, 2020) [14]. The proposed system reacts to this growing need by incorporating the means of machine learning that is robust to extract meaningful demographics based on audio data.

Among the main contributions of the work, it should be noted that convolutional and recurrent neural architecture can be particularly effective to simulate spectraltemporal speech dynamics (Lee *et al.*, 2019). The model can address the shortcoming of the traditional handcrafted acoustic features, which have been commonly used in the past literature, with the assistance of spectrogram representation and deep hierarchical features extraction (Garcia and Martinez, 2017) [4]. This end-to-end learning allows the network to learn small changes in the speech patterns, which can be linked to the demographic features, which has been widely in the recent publications on voice-based deep learning (Chen and Liu,

2020; Kim *et al*., 2018) [2, 7].

The second important aspect that was presented in the study is the importance of wide and balanced data sets. Since demographic prediction requires a minor variation of vocal characteristics of the speakers, the model can be better generalized by the samples of the speakers of various age groups and genders (Gupta *et al*., 2021) [5]. According to the present study, the use of different data is increasing the efficiency of neural models in practice by a significant margin (Brown *et al*., 2018) [1].

It was also found out that the proposed architecture was also effective as the results of the experiment confirm. The measures of the accuracy, precision, recall, and F1-score demonstrate that the deep learning model is never inferior to the traditional classifiers, and it has a better capability to learn the characteristics (Nguyen and Andre, 2019) [12]. The results are consistent with the overall evidence of speech analysis research, where deep neural networks were proved to be useful in demographic and speaker-related predictions (Chen *et al*., 2019; Wang and Zhang, 2015) [3, 20]. All in all, the discussion defines the practical implications of the work. Voice-based demographic prediction will enable marketers to design more custom and contextual marketing programs, which will lead to user satisfaction and marketing performance (Kim, S., *et al*., 2020) [8]. The study has a good contribution to the field and contributes to the newly gained value of deep learning in the creation of intelligent and customized digital ad space.

**Table 1:** Performance Evaluation Metrics for Age and Gender Prediction

| Metrics | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|
| Age Prediction | 0.92 | 0.91 | 0.93 | 0.92 |
| Gender Prediction | 0.88 | 0.87 | 0.89 | 0.88 |

## Conclusion

In conclusion, the study concerning The Age and Gender Prediction based on Human Voice to create Personalized Ads has demonstrated the efficiency and feasibility of predicting demographic information with the help of direct audio data and deep neural networks. The article is a significant addition to the study of personalized advertising, where the estimations of age and gender play a vital role in the process of customizing the advertisements to the particular users. Results suggest that the suggested model is of high excellence as it was justified by the high rate of the accuracy, precision, recall, and the F1 score. These findings confirm the possibility of the model to detect the hidden dynamics of human voice that underscores that the model can be used to improve future targeted advertising solutions. The findings indicate the potential of further and precise customization of advertisements that will provide more positive user experiences in the digital form. This study can render the process of predicting demographic data scalable and efficient by eliminating the necessity to program the creation of features manually, and allowing the model to discover the right features on its own. The effectiveness of the deep learning model suggests a paradigm shift in the personalised advertising sector, to offer viability to the advertisers and marketers with more effective and personalised outreach strategies.

## References


1. Brown C, Smith J, Taylor R, *et al*. A comprehensive survey of methods for demographic prediction from voice. J Artif Intell Res. 2018;25(2):567-589.
2. Chen W, Liu X. Voice-based gender and age prediction using convolutional neural networks. Neurocomputing. 2020;22(11):2456-2467.
3. Chen X, Wang Y, Li M, *et al*. Deep neural networks for age estimation from speech signals. IEEE Signal Process Lett. 2019;21(8):1011-1015.
4. Garcia M, Martinez T. Predicting age and gender from acoustic features using support vector machines. Expert Syst Appl. 2017;42(15-16):6358-6365.
5. Gupta N, Singh A, Kumar R, *et al*. A survey on deep learning techniques for audio-based gender and age classification. J Ambient Intell Humaniz Comput. 2021;40(3):789-802.
6. Han J, Lee S, Kim H, *et al*. Multi-task learning for joint age and gender prediction from voice. Comput Speech Lang. 2021;65:101118.
7. Kim J, Park H, Lee M, *et al*. Exploring the role of recurrent neural networks in voice-based demographic prediction. Comput Speech Lang. 2018;40(8):132-147.
8. Kim S, Choi Y, Jung H, *et al*. Adaptive personalized advertising through deep learning from audio data. J Interact Mark. 2020;15(7):123-136.
9. Lee Y, Park J, Kim S, *et al*. Voice-based gender and age classification using deep neural networks. J Mach Learn Res. 2019;28(6):890-912.
10. Li X, Zhang Y, Wang Z, *et al*. Gender classification from speech using spectral and prosodic features with SVM. Inf Sci. 2014;32(4):567-580.
11. Nguyen P, Le T, Vu H, *et al*. Age and gender prediction from voice: A comparative analysis of machine learning techniques. Inf Sci. 2018;32(4):567-580.
12. Nguyen T, Andre E. CNN–LSTM hybrid models for voice-based age and gender prediction. Neural Netw. 2019;114:134-144.
13. Pampapathi BM, Guptha N, Hema MS. Towards an effective deep learning-based intrusion detection system in the internet of things. Telemat Inform Rep. 2022;7:100009.
14. Patel R, Gupta S. Enhancing ad personalization through voice-based demographic prediction. Int J Hum Comput Interact. 2020;35(4):789-802.
15. S K S, Bharathi SH. Improving the performance of speech recognition feature selection using Northern Goshawk Optimization. In: 2022 International Interdisciplinary Humanitarian Conference for Sustainability (IIHC); 2022 Nov 18-19; Bengaluru, India. IEEE; 2022. p. 556-559.
16. Santosh KS, Bharathi SH. Non-negative matrix factorization algorithms for blind source separation in speech recognition. In: 2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT); 2017 May 19-20; Bengaluru, India. IEEE; 2017. p. 2242-2246.
17. Sharma A, Verma R. Towards more accurate demographic prediction: A case study on voice-based age and gender classification. Pattern Recognit Lett. 2016;29(9):1345-1355.
18. Shrividya Guruprasad SH, Bharathi S, Anto Ramesh Delvi D. Effective compressed sensing MRI reconstruction via hybrid GSGWO algorithm. J Vis Commun Image Represent. 2021;80:103274.

19. Smith J, Johnson A. Advancements in deep learning for audio analysis. IEEE Trans Neural Netw. 2019;30(5):1234-1256.
20. Wang L, Zhang Q. A comparative study of feature learning methods for audio-based gender prediction. IEEE/ACM Trans Audio Speech Lang Process. 2015;18(3):456-468.

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