

CLAPMETRICS: DECODING USERS' GENDER AND AGE THROUGH SMARTWATCH GESTURE DYNAMICS

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PRESENTATION OVERVIEW

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- 2 Existing Methods and Their Limitations
- 3 ClapMetrics
- 4 Conclusions

Why Age and Gender Estimation?

WHY AGE AND GENDER ESTIMATION?

PERSONALIZED USER EXPERIENCES

- **Streaming Services:** Platforms like **Netflix** could recommend **age and gender-specific content**, such as animated films for younger users or true crime series for adults.

STREAMING SERVICES



WHY AGE AND GENDER ESTIMATION?

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- **Streaming Services:** Platforms like **Netflix** could recommend **age and gender-specific content**, such as animated films for younger users or true crime series for adults.
- **Health and Fitness Apps:** Exercise recommendations in apps like MyFitnessPal or Strava could **adjust based on age**—**strength training for younger users and flexibility exercises for older ones.**

STREAMING SERVICES



FITNESS APP



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- **Health and Fitness Apps:** Exercise recommendations in apps like MyFitnessPal or Strava could **adjust based on age**—**strength training for younger users and flexibility exercises for older ones**.
- **News Apps:** News aggregators like Flipboard could suggest content relevant to different demographics, **like career advice for younger users and financial planning for older users**.

STREAMING SERVICES



FITNESS APP



NEWS



WHY AGE AND GENDER ESTIMATION?

INCREASED SECURITY AND AUTHENTICATION

- **Banking Security:** Age and gender estimation can provide an additional verification layer in mobile banking apps, such as **confirming identity for secure logins and preventing fraud.**

BANKING SECURITY



WHY AGE AND GENDER ESTIMATION?

INCREASED SECURITY AND AUTHENTICATION

- **Banking Security:** Age and gender estimation can provide an additional verification layer in mobile banking apps, such as **confirming identity for secure logins and preventing fraud.**
- **Workplace Authentication:** Offices and secure facilities can use age and gender data to add a **behavioral biometric layer to traditional security protocols, enhancing employee verification.**

BANKING SECURITY



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- **Banking Security:** Age and gender estimation can provide an additional verification layer in mobile banking apps, such as **confirming identity for secure logins and preventing fraud.**
- **Workplace Authentication:** Offices and secure facilities can use age and gender data to add a **behavioral biometric layer to traditional security protocols, enhancing employee verification.**
- **Healthcare Access Control:** Hospitals and healthcare systems could integrate age and gender checks in wearables **to protect patient data and control access to sensitive areas.**

BANKING SECURITY



HEALTHCARE ACCESS CONTROL



EXISTING TECHNIQUES AND THEIR LIMITATIONS

FACIAL FEATURES

- **Strengths:** High accuracy in controlled environments; widely applicable in consumer and security applications.
- **Limitations:** Sensitive to lighting and angle; **privacy concerns**; accuracy may degrade with aging. **It is an Intrusive way!**



Virmani, Deepali, Tanu Sharma, and Muskan Garg. "GAPER: gender, age, pose and emotion recognition using deep neural networks." *Advances in Electromechanical Technologies: Select Proceedings of TEMT 2019*. Springer Singapore, 2020. 287-297.

EXISTING TECHNIQUES AND THEIR LIMITATIONS

FINGERPRINT ANALYSIS

- **Strengths:** Accurate and consistent with unique fingerprint patterns; works well in secure environments.
- **Limitations:** Requires physical contact, which may raise hygiene concerns; age estimation is limited. **It is an Intrusive way!**

Spanier, Assaf B., et al. "Enhancing Fingerprint Forensics: A Comprehensive Study of Gender Classification Based on Advanced Data-Centric AI Approaches and Multi-Database Analysis." *Applied Sciences* 14.1 (2024): 417.

VOICE ANALYSIS

- **Strengths:** Non-intrusive and works with audio data alone; useful in hands-free applications.
- **Limitations:** Accuracy affected by background noise, vocal health, and language dependency.

Foggia, Pasquale, et al. "Identity, Gender, Age, and Emotion Recognition from Speaker Voice with Multi-task Deep Networks for Cognitive Robotics." *Cognitive Computation* (2024): 1-11.

CLAPMETRICS: Decoding Users' Gender and Age Through Smartwatch Gesture Dynamics

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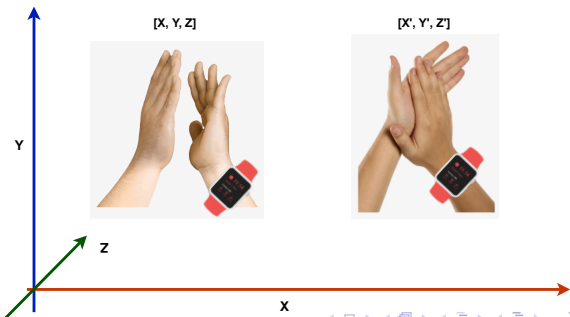
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INTRODUCTION

- We propose the exploitation of **arm's micro-movements generated during the course of clapping action** to estimate age and gender of wearer/clapper.
 - **Strengths:** Completely un-intrusive, accurate, user-friendly, does not require any additional physical contact,
 - **Limitations:** Might be too difficult in some scenarios (although, a faint clap would be ok).



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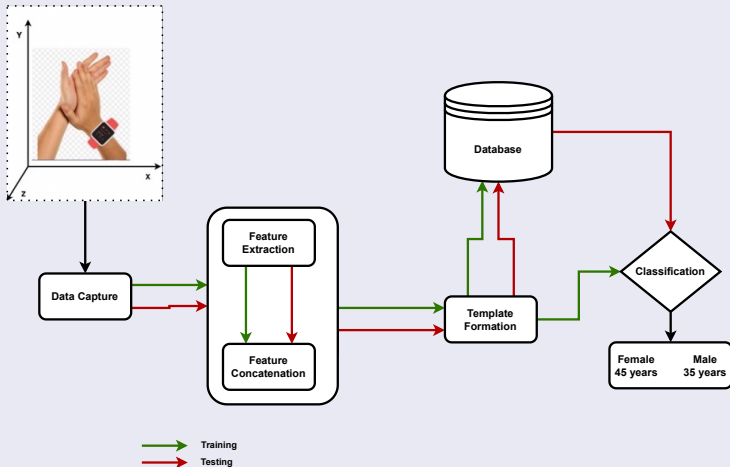
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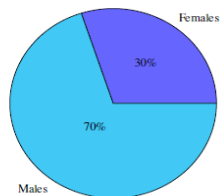
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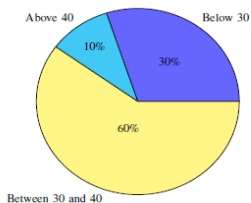
DATA COLLECTION

- **20 participants**
 - students and researchers
- **3 body posture**
 - Sitting, Standing, and Walking
- **Signup**
 - 100-sec data in each of the posture
 - In total, 3000s of data (**Used in this paper**)
- **Sign-in**
 - 100-sec data in any of the posture
 - In total, 2000s of data

SUBJECTS



(a) Gender



(b) Age

FEATURE EXTRACTION

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SENSOR DATA

- **Sensors are 3-dimensional: 4D data from accelerometer and gyroscope**

$$m = \sqrt{\text{sensor}[x]^2 + \text{sensor}[y]^2 + \text{sensor}[z]^2} \quad (1)$$

STATISTICAL FEATURES

- **41 statistical features from each sensor**
 - **Min (4+4), Max (4+4), Mode (4+4), Median (4+4), Mean (4+4), Variance (4+4), Skewness (4+4), Kurtosis (4+4), Correlation (3+3), Abs (3+3), Cosine similarity (3+3)**

CLASSIFIER SELECTION AND OPTIMIZATION

CLASSIFIERS

- **BN**: Probabilistic graphical models representing variables and their conditional dependencies.
- **KNN**: Non-parametric method known for simplicity and effectiveness in classification.
- **RF**: Ensemble learning method constructing multiple decision trees for accurate and stable predictions.
- **DNN**: Advanced machine learning classifier, particularly with Convolutional Neural Networks (CNNs).

PARAMETER OPTIMIZATION

Classifier	Parameters	Range of Parameters	Best Hyperparameter	Best Validation Accuracy (%)
KNN	<i># of neighbors</i>	1 to 50 (increment=5)	1	(Age: 99.38) (Gender: 96.31)
RF	<i># of estimators</i>	100 to 1000 (increment=100)	200	(Age: 98.20), (Gender: 96.13)
DNN	<i>num.layers</i> <i>num.units</i> <i>learning_rate</i>	2 to 10 (increment=1) 32 to 512 (increment=32) 0.01, 0.001, 0.0001	3 288, 512, 384 0.001	(Age: 96.93) (Gender: 95.70)

CLASSIFICATION TASKS AND DATA PARTITIONING

GENDER ESTIMATION

- Formulated as a **binary classification task: male or female**.
- Simplifies the model's decision-making process for focused gender estimation.

AGE ESTIMATION

- Treated as a **three-class classification problem to capture distinct age groups**.
- Tailors classifiers to recognize and differentiate between specific age ranges.

DATA PARTITIONING

- Dataset split into **training (50%) and test (50%) sets for balanced learning and validation**.
- Training set further divided: **66% for training, 34% for validation**.

PARAMETER OPTIMIZATION

- Conducted exclusively on **the training set to fine-tune hyperparameters**.
- Optimized parameters applied to classifiers, trained on the full training set, and **evaluated on the test set**.

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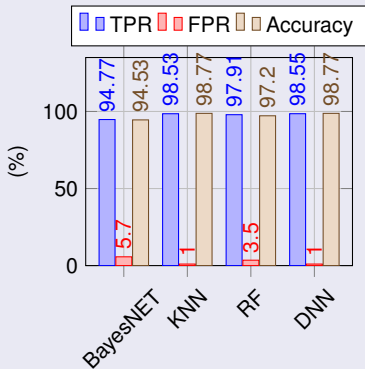
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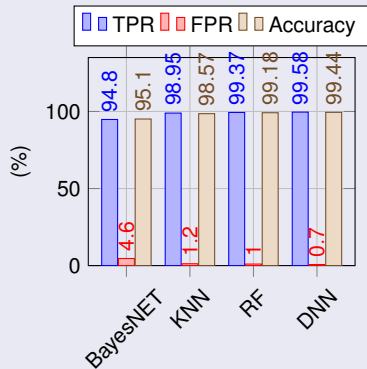
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GENDER ESTIMATION



AGE ESTIMATION



DEEPCAP: CONCLUSIONS & WAY FORWARD

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- **We propose a user-friendly, un-intrusive, accurate and DNN-powered age and gender estimation using smartwatch**
- **DNN achieves 98.77% and 99.44% accuracies for gender of age estimation from clapping movements**

WAY FORWARD

- **Final proof-of-the-concept implementation**
- **Performance Analysis (computation, memory, testing time)**
- **Security analysis (random, mimic, etc)**
- **Usability analysis (SUS, etc.)**

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Thanks! Questions?