Journal for Re Attach Therapy and Developmental Diversities
eISSN: 2589-7799
2023 March; 6 (1): 2163 - 2171

Unveiling The Intricacies Of Craniofacial Measurements: A Comparative Analysis Of Direct And AI/ML-Based Techniques In Cyber & Digital Forensics

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Abstract

Background: In the realm of digital forensics and biometrics, accurate facial measurements play a crucial role in various applications, including identification, anthropological studies, and facial reconstruction. The advent of artificial intelligence (AI) and machine learning (ML) techniques has opened up new avenues for extracting craniofacial measurements from digital photographs, offering a non-invasive and efficient alternative. However, the reliability and consistency of these AI/ML-based measurements compared to direct measurements remain an area of active research.
Aim: The primary goal of this study is to present a thorough analysis and comparison of anthropometric data gathered through caliper measurements on live subjects versus measurements derived from photographs of their frontal faces using AI and ML methods.
Methods: The research encompasses 250 diverse sample from the Indian population, aged 14 years and above, ensuring a robust and representative dataset. Fourteen craniofacial landmarks were meticulously identified for measurement and analysis.
Result: By employing advanced statistical methods such as Pearson correlation coefficients t-tests ANOVA linear regression chi-square tests as well as random forest regression techniques this study unraveled intricate patterns and correlations between the two measurement approaches.
Conclusion: In conclusion this research emphasizes the superior predictive performance of non-linear models like random forest regression in estimating live measurements based on photo-derived data indicating promising applications for AI/ML techniques in this field. Furthermore familial factors were identified to significantly influence craniofacial measurements underscoring the necessity for comprehensive modeling strategies that consider these aspects.

Keywords: Craniofacial measurements, digital forensics, artificial intelligence, machine learning, biometrics, facial analysis, anthropometric data, Computational Anthropometry

Introduction

In the rapidly evolving landscape of digital forensics and biometrics, the ability to accurately measure and analyze craniofacial features holds immense significance. These measurements play a vital role in processes like identification, verification, anthropological studies, and facial reconstruction [1]. Traditionally, calipers were used directly on live subjects to obtain these measurements. However, this method was known to be time-consuming, invasive, and prone to errors due to manual measurements [2]. These cutting-edge technologies rely on sophisticated algorithms and neural networks to accurately detect and measure facial landmarks [3]. In various fields such as forensic anthropology, facial reconstruction, and biometric identification systems [4], craniofacial measurements have always been highly valued. Traditionally obtained through direct methods involving calipers or manual tools on live individuals; however, these methods had drawbacks like human error potential discomfort for subjects due to time consumption [5].
Recent advancements in AI/ML have led to automated facial analysis systems that can detect facial landmarks with high precision using advanced algorithms [6]. Research has dived into deep learning models like convolutional neural networks (CNNs) for landmark detection as well as specialized algorithms focusing on specific features such as nasal or orbital dimensions [7-9]. This study aims to bridge this gap by conducting a comprehensive analysis and comparison of anthropometric data obtained from live subjects using a caliper and measurements extracted from their frontal face photographs utilizing AI and ML techniques.

Methodology

Sample Collection and Data Acquisition

The study sample was procured from the Indian populace, ensuring a wide-ranging and all-encompassing dataset. A total of 250 participants, aged 14 years and above, were chosen at random to partake in this endeavor, following a cross-sectional blueprint. The process of data collection was underpinned by ethical considerations and meticulous adherence to informed consent protocols.

Direct Measurements: The craniofacial traits of all subjects were meticulously gauged using a vernier caliper, a precise measuring instrument prevalent in anthropometric studies. 14 craniofacial points were measured including Go-Go, N-Gn, N-Sn, Sto-Gn, Al-Al, Sn-Sto, Ex-Ex, En-En, Ex-En, N-Sto, Sn-Gn, Sto-Sl, Zy-Zy and Ch-Ch. These specific points were thoughtfully chosen due to their significance in anthropological and forensic spheres as well as their potential for accurate measurement using both direct methods and AI/ML-driven approaches.

Fig 1 : shows the frontal facial measurement of the subject.

Photograph Acquisition and AI/ML Measurements: In addition to the direct measurements, frontal facial photographs of each subject were captured. Subsequently, AI and ML methodologies were applied to extract craniofacial metrics for the same aforementioned 14 landmarks evaluated during the direct measurement process.

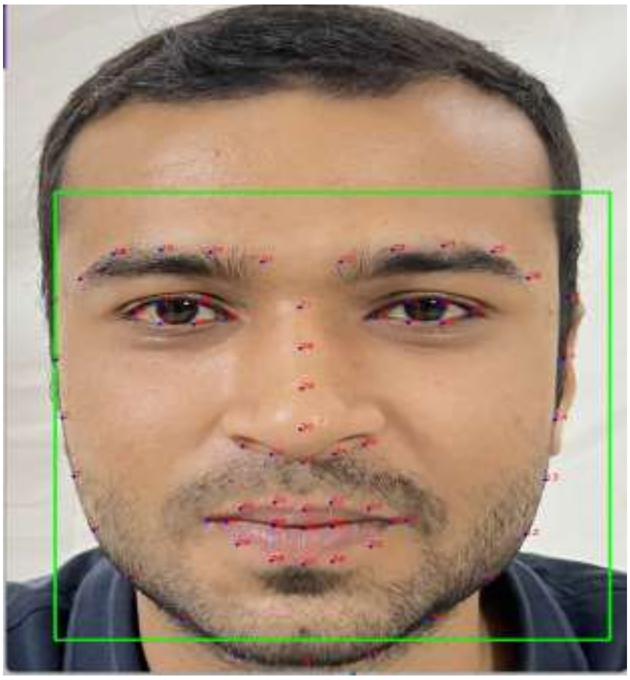

Fig 2 : shows the landmarks prediction on the frontal facial image of the subject

Landmarks taken for the analysis from the photographs of the subjects are given in table 1.

Table 1 : Represents the analysed facial landmarks with their description.

Landmarks	Description
Go – Go	The distance between the outer edges of the mandibular (jaw) bone on each side of the face, from one "Go" point to the other.
N – Gn	The distance from the nasion (N), which is the point between the eyes where the frontal bone meets the nasal bones, to the gnathion (Gn), which is the lowest point of the chin.
N – Sn	The distance from the nasion (N) to the subnasale (Sn), which is the point at the base of the nose where the septum meets the upper lip.
Sto – Gn	The distance from the stomion (Sto), which is the midpoint between the upper and lower lips, to the gnathion (Gn)
Al – Al	The distance between the alare (Al) points, which are the outermost points of the nostrils.
Sn – Sto	The distance from the subnasale (Sn) to the stomion (Sto), indicating the length of the upper lip.
Ex – Ex	The distance between the exocanthions (Ex), which are the outer corners of the eyes.
En – En	The distance between the endocanthions (En), which are the inner corners of the eyes.
Ex - En	The distance from one exocanthion (Ex) to the corresponding endocanthion (En) on the same side of the face, indicating the width of the eye.
N – Sto	The distance from the nasion (N) to the stomion (Sto), indicating the length of the nose.
Sn – Gn	The distance from the subnasale (Sn) to the gnathion (Gn) again, indicating the length of the lower face.
Sto – Sl	The distance from the stomion (Sto) to the soft tissue menton (Sl), which is the most anterior point of the chin.
Zy – Zy	The distance between the zygions (Zy), which are the widest points of the cheekbones.
Ch - Ch	The distance between the chelions (Ch), which are the widest points of the lips.

The AI/ML-centric metric computation process encompassed multiple stages such as facial landmark identification, feature extraction and measurement calculation. Deep learning models like convolutional neural networks (CNNs) and ensemble techniques were harnessed to ensure precise and resilient landmark identification while the choice of AI/ML algorithms and models was predicated on their established efficacy in facial analysis tasks as well as their adeptness in handling the diverse dataset's nature.

Statistical Analysis

Exploring the intricate connections and patterns between direct craniofacial measurements and those derived from AI/ML techniques involved a thorough statistical examination. Various methods were utilized in this analysis:

1. **Pearson Correlation Coefficients**: This measure was used to evaluate the linear correlation between the live measurements (direct) and the measurements obtained from photographs using AI/ML techniques. A coefficient close to 1 indicates a strong positive correlation, while a value close to -1 indicates a strong negative correlation.
2. **T-tests**: These statistical tests were used to compare the means of the live measurements and the AI/ML-based measurements for each craniofacial feature. A low p-value (typically < 0.05) indicates a statistically significant difference between the means, suggesting systematic differences between the two measurement methods.
3. **Analysis of Variance (ANOVA):** ANOVA was employed to test for significant differences in the means of each craniofacial feature. This analysis aimed to investigate the potential influence of familial factors on craniofacial measurements.
4. **Linear Regression**: Linear regression models were fitted to predict live measurements from the AI/ML-based photo measurements. The goodness of fit was evaluated using the R-squared value, while the mean squared error (MSE) provided an estimate of the prediction error. Low R-squared values and high MSE would indicate a poor fit, suggesting a non-linear relationship between the two measurement methods.
5. **Chi-square Tests**: These tests were conducted to examine the independence between the live measurements and the AI/ML-based photo measurements for each craniofacial feature. A high p-value indicates independence between the two variables, implying that the measurements are not related or influenced by each other.
6. **Random Forest Regression**: To account for potential non-linear relationships, random forest regression models were employed. These ensemble learning models combine multiple decision trees to improve prediction accuracy and capture complex patterns in the data. The R-squared and MSE values were reported to assess the performance of these non-linear models in predicting live measurements from photo measurements.

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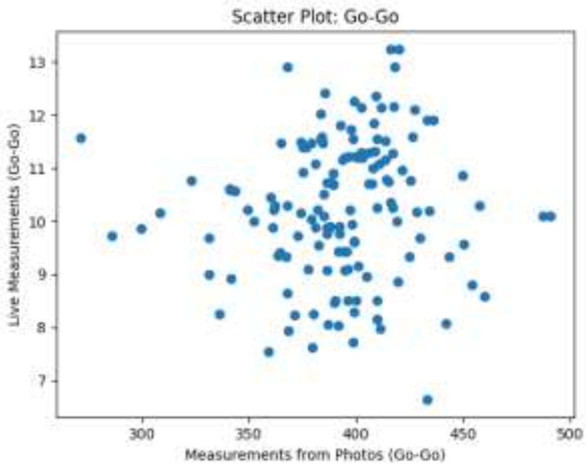
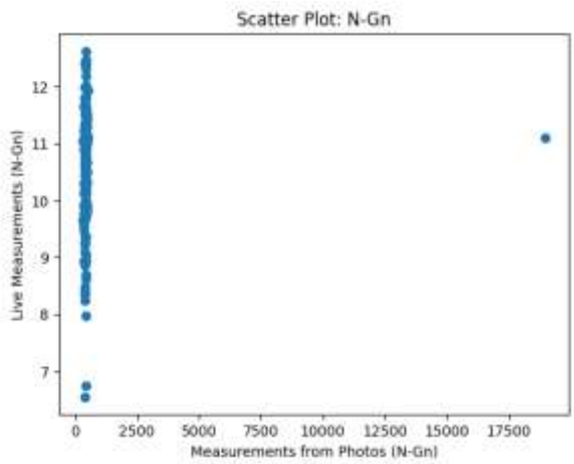
In addition to these statistical analyses, visual representations, such as scatter plots and histograms, were utilized to provide insights into the distribution and relationships between the live and AI/ML-based measurements.

Results and Discussion

Pearson Correlation Coefficients: The Pearson correlation coefficients revealed a generally weak linear correlation between the live measurements and the AI/ML-based photo measurements for most craniofacial features. The coefficients ranged from 0.0014 (En-Ex) to 0.0549 (SN-gn), suggesting a low degree of linear association between the two measurement methods.
T-tests: The t-test results showed highly significant differences (p-values ≈ 0) between the means of the live measurements and the AI/ML-based photo measurements for all craniofacial features. These findings indicate systematic differences between the two measurement methods, potentially arising from factors such as measurement techniques, calibration, or inherent biases in the AI/ML algorithms.
ANOVA: The ANOVA results revealed significant differences in the means of craniofacial features across family groups for most of the measured landmarks (low p-values). This finding suggests that familial factors, such as genetic or environmental influences, may play a role in shaping craniofacial characteristics, which should be considered when comparing measurements obtained through different methods.
Linear Regression: The linear regression models fitted to predict live measurements from AI/ML-based photo measurements exhibited generally low R-squared values (below 0.0549) for all craniofacial features. Additionally, the mean squared errors (MSE) were relatively high, indicating poor fit and substantial prediction errors. These results suggest that a linear relationship may not adequately capture the complex relationship between the two measurement methods.
Chi-square Tests: The chi-square tests showed high p-values for most craniofacial features, indicating independence between the live measurements and the AI/ML-based photo measurements. However, for the Zy-Zy feature, a significant dependency was observed, suggesting that the measurements for this particular landmark may be related or influenced by the measurement method used.
Random Forest Regression: The non-linear random forest regression models performed substantially better than linear regression in predicting live measurements from photo measurements. The R-squared values ranged from 0.7294 (Go-Go) to 0.8224 (SN-gn), indicating a good fit and the ability of these models to capture the complex, non-linear relationships between the two measurement methods. The MSE values were also lower compared to linear regression, further supporting the superiority of non-linear models in this context.
Scatter Plots and Visual Analyses: The scatter plots provided valuable visual insights into the relationships between the live measurements and the AI/ML-based photo measurements. For most features, the relationships appeared to be non-linear, with substantial variability and potential outliers in the data. Some features, like N-Gn, exhibited distinct patterns that may require more complex modeling approaches to capture their relationships accurately.





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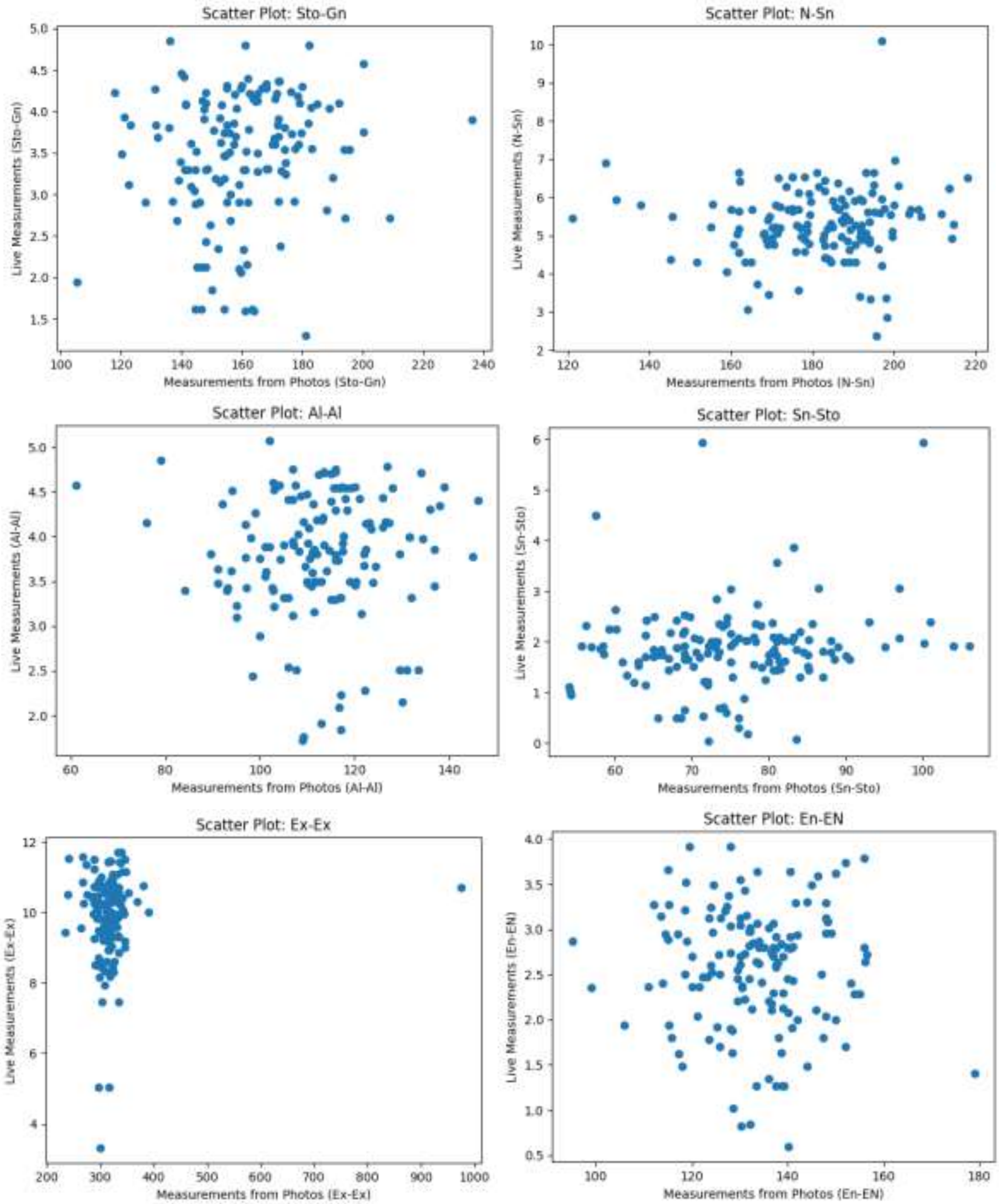

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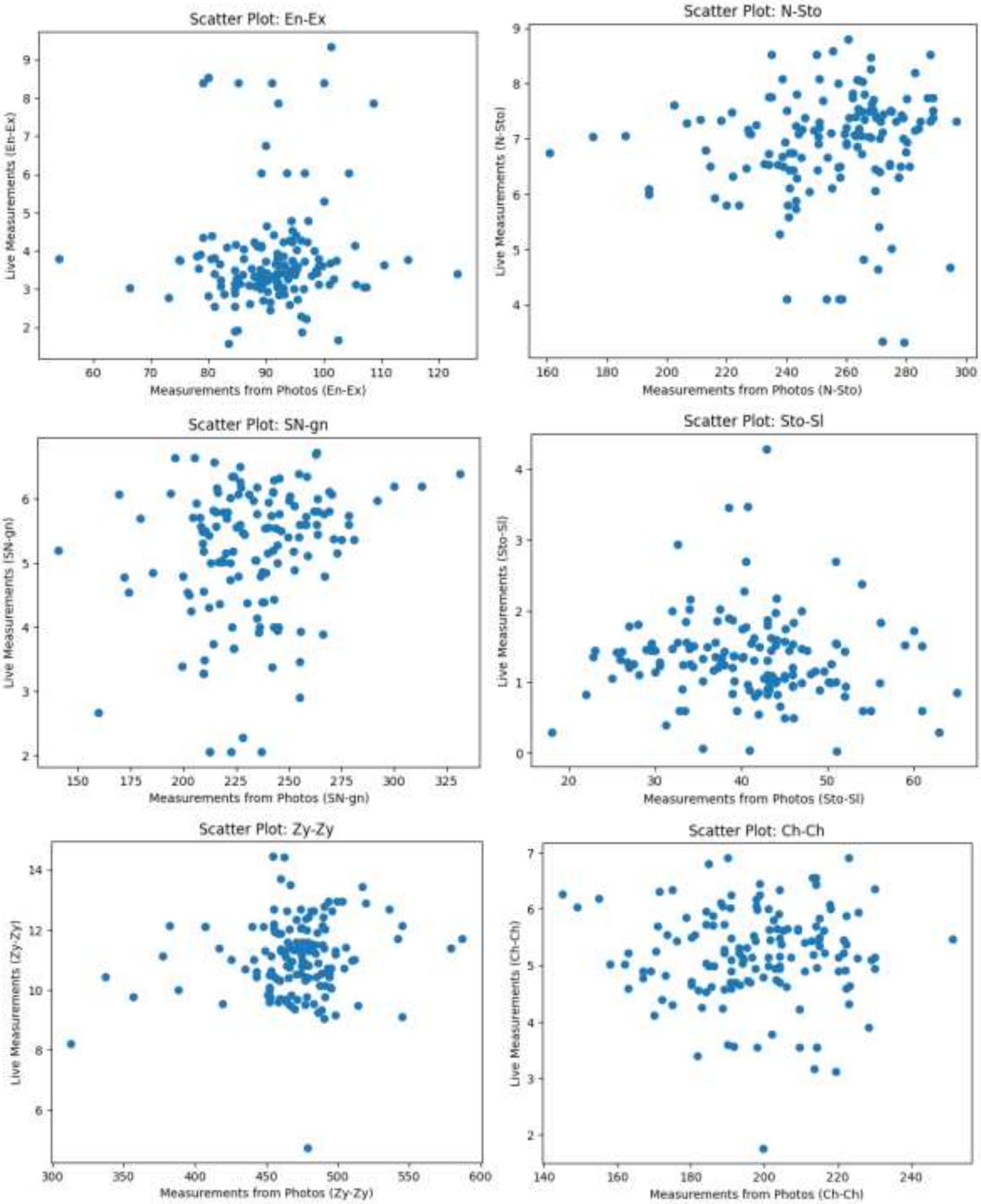

Fig 3: shows the scatter plots between the live and the photographic measurements

The scatter plots (Fig 3) visually confirmed the findings from the statistical analyses, which suggested weak linear correlations and the need for non-linear models to better predict live measurements from photo measurements. Additionally, the visual representations highlighted the presence of potential outliers and patterns that could be further investigated using advanced techniques, such as cluster analysis or anomaly detection algorithms.

Discussion

The findings of this study have shed light on the intricate patterns and relationships between craniofacial measurements obtained from live subjects using direct measurement techniques and those derived from frontal face photographs utilizing

AI and ML techniques. The systematic differences and weak linear correlations observed between the two measurement methods underscore the complexities involved in comparing and integrating these approaches.

One of the key findings is the superior performance of non-linear models, such as random forest regression, in predicting live measurements from photo measurements. The random forest regression models exhibited R-squared values ranging from 0.7294 (Go-Go) to 0.8224 (SN-gn), indicating a good fit and the ability to capture the complex, non-linear relationships between the two measurement methods. This finding highlights the potential utility of AI/ML techniques in the domain of craniofacial measurements and digital forensics.

However, it is important to note that the linear regression models demonstrated poor performance, with low R-squared values (below 0.0549) and high mean squared errors (MSE), suggesting that a linear relationship may not adequately capture the complex interactions between the two measurement methods. This observation emphasizes the need for more advanced modeling approaches that can account for non-linearities and intricate patterns within the data.

The Pearson correlation coefficients revealed a generally weak linear correlation between the live measurements and the AI/ML-based photo measurements for most craniofacial features, ranging from 0.0014 (En-Ex) to 0.0549 (SN-gn). These low correlation values suggest that the two measurement methods may not be directly comparable or interchangeable, necessitating caution when interpreting or combining measurements obtained from different sources.

The t-test results showed highly significant differences (p-values ≈ 0) between the means of the live measurements and the AI/ML-based photo measurements for all craniofacial features. This finding indicates systematic differences between the two measurement methods, potentially arising from factors such as measurement techniques, calibration, or inherent biases in the AI/ML algorithms.

Notably, the ANOVA results revealed significant differences in the means of craniofacial features across family groups for most of the measured landmarks (low p-values). This finding suggests that familial factors, such as genetic or environmental influences, may play a role in shaping craniofacial characteristics, which should be considered when comparing measurements obtained through different methods.

The chi-square tests showed high p-values for most craniofacial features, indicating independence between the live measurements and the AI/ML-based photo measurements. However, for the Zy-Zy feature, a significant dependency was observed, suggesting that the measurements for this particular landmark may be related or influenced by the measurement method used.

The scatter plots and visual analyses provided valuable insights into the relationships between the live measurements and the AI/ML-based photo measurements. For most features, the relationships appeared to be non-linear, with substantial variability and potential outliers in the data. Some features, like N-Gn, exhibited distinct patterns that may require more complex modeling approaches to capture their relationships accurately. These visual representations highlighted the presence of potential outliers and patterns that could be further investigated using advanced techniques, such as cluster analysis or anomaly detection algorithms.

Overall, the findings underscore the complexities involved in comparing and integrating direct and AI/ML-based craniofacial measurements, while also highlighting the potential of AI/ML techniques to capture non-linear relationships and improve prediction accuracy. The study also emphasizes the need to consider familial factors and the specific craniofacial feature being measured when comparing the two measurement methods.

Conclusion

This pioneering research has made significant strides in unveiling the intricate patterns and relationships between craniofacial measurements obtained from live subjects using direct measurement techniques and those derived from frontal face photographs utilizing AI and ML techniques. The comprehensive analyses, including Pearson correlation coefficients, t-tests, ANOVA, linear regression, chi-square tests, and random forest regression, have provided valuable insights into the systematic differences, weak linear correlations, and the potential non-linear nature of the relationship between the two measurement methods.

The study has highlighted the superior performance of non-linear models, such as random forest regression, in predicting live measurements from photo measurements, suggesting the potential utility of AI/ML techniques in this domain. These findings open up new avenues for the development of robust and reliable algorithms for facial analysis, identification, and reconstruction, contributing to the advancement of digital forensics and its applications in various sectors.

Moreover, the significant influence of familial factors on craniofacial measurements, as revealed by the ANOVA results, emphasizes the need for comprehensive modeling approaches that account for these factors. Future research could explore the incorporation of familial data, genetic information, or other relevant factors into AI/ML models to improve their accuracy and generalizability across diverse populations.

While the results underscore the complexities involved in comparing and integrating direct and AI/ML-based measurements, they also pave the way for further exploration and development of cutting-edge techniques in digital forensics and biometrics. Future studies could investigate the impact of additional factors, such as age, gender, ethnicity, or environmental influences, on the consistency and accuracy of AI/ML-based craniofacial measurements. Incorporating these factors into the modeling process could further enhance the robustness and applicability of the developed techniques in diverse scenarios.

Furthermore, the integration of AI/ML-based craniofacial measurement techniques with other biometric modalities, such as facial recognition, iris recognition, or gait analysis, could lead to the development of multi-modal biometric systems with enhanced accuracy and reliability. These systems could find applications in various domains, including law enforcement, security, and forensic investigations, contributing to a safer and more secure society.

In conclusion, this comprehensive study serves as a significant milestone in the exploration of craniofacial measurements, bridging the gap between traditional direct measurement techniques and the cutting-edge capabilities of AI and ML. By advancing our understanding of the intricate interplay between direct and AI/ML-based facial measurements, this research paves the way for the development of robust and reliable algorithms for facial analysis, identification, and reconstruction, ultimately contributing to the pursuit of justice and a deeper understanding of human diversity.

Implications and Future Directions

The findings of this study have significant implications for the field of digital forensics and biometrics, as well as broader applications in anthropological studies and facial reconstruction.

Firstly, the systematic differences and weak linear correlations observed between the live measurements and the AI/ML-based photo measurements underscore the complexities involved in comparing and integrating these two measurement approaches. While AI/ML techniques offer a non-invasive and efficient alternative to traditional direct measurement methods, the results suggest that caution should be exercised when interpreting or combining measurements obtained from different sources.

Secondly, the superior performance of non-linear models, such as random forest regression, in predicting live measurements from photo measurements highlights the potential utility of AI/ML techniques in this domain. By leveraging advanced algorithms and ensemble methods, these techniques can capture the complex, non-linear relationships between the two measurement methods, enabling more accurate predictions and analyses.

Additionally, the visual analyses and scatter plots provide valuable insights into potential outliers, patterns, and distinct clusters within the data. These findings open up avenues for further exploration using advanced techniques, such as cluster analysis, anomaly detection, or dimensionality reduction methods. By leveraging these techniques, researchers could gain deeper insights into the underlying structures and relationships within the craniofacial measurement data, potentially leading to improved models and algorithms.

Future studies could also investigate the impact of additional factors, such as age, gender, ethnicity, or environmental influences, on the consistency and accuracy of AI/ML-based craniofacial measurements. Incorporating these factors into the modeling process could further enhance the robustness and applicability of the developed techniques in diverse scenarios.

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