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Hybrid Deep Learning and Swarm Intelligence Framework for Accurate Age Estimation from Wrinkles

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ABSTRACT

Facial wrinkles, influenced by skin type and muscle contraction, are vital indicators of aging. Accurate age estimation from these patterns has significant applications in healthcare, security, and marketing. This paper introduces a robust framework integrating **Deep Learning with Hybrid Swarm Intelligence (DL-HSI)** for precise age prediction. Preprocessing ensures consistency in input data, followed by feature extraction using Histogram of Oriented Gradients (HOG). These features are fused and optimized through a hybrid approach leveraging Particle Swarm Optimization (PSO), enhancing feature selection and representation. Age group classification is performed using deep Convolutional Neural Networks (CNNs), which further refine predictions to estimate specific ages within groups. Experimental evaluation on the FG-NET dataset demonstrates the proposed method's superior performance, achieving higher accuracy and lower mean absolute error compared to traditional approaches. This unified framework underscores its potential for automated, reliable age estimation from facial wrinkles, offering valuable insights for diverse real-world applications. The proposed method achieves the ratio of accuracy by 98.08%, performance by 97.75%, MAE by 34.56%, processing time by 97.12% and future extraction efficiency by 96.34%.

Keywords: *Facial wrinkles, accurate age, CNN, HOG, PSO, swarm intelligence*

1. INTRODUCTION

Facial aging is one of the inevitable biological processes and can be seen in the presentation and development of wrinkles [1]. These wrinkles are allegedly influenced by genetics, environmental, and lifestyle factors which are the critical agents in evaluating a person's age [2]. The high degree of attention for age estimation through facial wrinkles is precipitated from its multiple applications in healthcare, security, and marketing in personalized terms [3]. For example, in healthcare sector, knowing of changes due to aging of human faces helps earlier in diagnosing [4]. The conditions-progeria and any other sort of skin issues whereas in security perspective, age prediction provides a support tool to boost up biometric technologies [5]. In general marketing strategy mainly employs age predication for choosing an appropriate consumer profile [6].

Normally age estimation strategies often use some sort of traditional approach like employing handcrafted feature and statistical approaches [7]. Although these approaches have led to important insights, they do not easily account for the complex variations and non-linear patterns of wrinkles, especially across different populations [8]. Deep learning has changed the landscape of this field, allowing the direct extraction of high-level features from raw data in an automatic fashion [9]. However, optimal performance is achieved only by overcoming challenges like variability in skin texture, lighting conditions, and individual aging trajectories [10]. This paper introduces a novel framework that combines hybrid swarm intelligence and deep learning to overcome these issues, providing more accurate and reliable age estimation [11]. The normalization of the given input images is carried out in the initial stage with a view to achieving homogeneity and robustness to noise [12].

HOG is used for feature extraction as it is appropriate for wrinkles structural details [13]. These features are further refined using a PSO driven integrated optimization strategy which together with other heuristic refinement techniques guarantees the inclusion of the most representative and the most discriminating features [14]. The proposed architecture is based on a CNN age group classification that refines guesstimates of age into categories of known age ranges while the system guarantees accuracy in the significant figures of outcome [15]. The evaluations using the popular FG-NET benchmark age estimation have shown promising results stemming from this framework [16]. It is realistic to say that the overwhelming results of its performance variants such as those of MAE values reflects its supremacy [17]. Automation and determining age using facial wrinkles using deep learning and swarm intelligence are reliable methods in this research [18].

Motivation: This paper deep learning and swarm intelligence should be used to address the deficiencies of conventional methods of age estimate techniques. By overcoming obstacles like feature variability and individual aging trends, accurate age prediction from wrinkles has the possibility to revolutionize healthcare, security, and marketing. This might lead to the diagnosis of diseases at an early stage, the improvement of biometric systems, and the implementation of customized consumer tactics.

Problem Statement: Because of differences in skin texture, lighting, and individual aging trends, it is still difficult to accurately estimate age from facial wrinkles. To fill these shortcomings, this paper combines deep learning with swarm intelligence to create a trustworthy automated system that improves the accuracy of age prediction for many real-world applications.

Contributions:

- Developed a hybrid approach combining PSO with heuristic enhancements to optimize wrinkle feature selection, ensuring improved representation and discrimination.
- Designed a deep CNN architecture for precise age group classification and fine-grained age estimation within groups, enhancing prediction accuracy.
- Demonstrated superior performance compared to traditional methods through extensive experimental evaluation, achieving higher accuracy and lower MAE in age estimation.

The remaining of this paper is structured as follows: In section 2, the related work of accurate age estimation from wrinkles is studied. In section 3, the proposed methodology of DL-HSI is explained. In section 4, the efficiency of DL-HSI is discussed and analysed. Finally, in section in the paper is concluded with the future work.

2. RELATED WORK

Changes in fundamental facial structures brought about by gravity, sun exposure, and bone reformation, as well as the development of wrinkles on the surface of the face, are hallmarks of the ageing process. The acquisition of an appropriate training and testing dataset is the first stage in developing an automated age estimate algorithm. There is a plethora of freely accessible datasets that include tagged samples of different lighting, head positions, and environmental factors.

Facial Age Estimation using Machine Learning Technique (MLT):

Academics have been captivated by the intriguing field of automatic age estimate from face photographs, which falls under the umbrella of machine learning. As a supplementary function for user filtering or identification, age estimation models are used by many human-computer interaction applications. There are many uses for automated age estimate, but there are also challenges in developing such a system, such as inconsistencies in the data, the fact that everyone ages differently, and poor-quality face photos by ELKarazle, K. et al., [19].

A comprehensive overview of the current state of the art in automated age estimate model creation, including the conventional approaches, benchmark datasets, and recently suggested literature that provide novel methodologies. The paper concludes with a presentation and discussion of the most common criteria for evaluating age estimate methods. Along with the poll, we also cover the gaps in the literature review and provide suggestions for future studies by Ali, S. M. et al., [20].

Facial Age Estimation using Artificial Intelligence (AI):

It's not uncommon to use AI to determine a person's chronological age only by looking at their skin. It is common practice to use facial photos as biometric data while building CNN models. Still, a person's hands reveal a lot about their age. Dorsal hand pictures frontal face images, we trained two CNNs to predict CA only from hand images. In both theoretical and applied studies of aging, age prediction using human photographs is of paramount importance by Georgievskaya, A. et al., [21].

The characteristics that went into the CNN models by either making certain parts of the hand and face less visible or making other parts more apparent in certain areas. The most crucial regions for facial age prediction were those around the mouth and the inner corner of the eye. One important factor in determining age for the hands was the texture of the knuckles. As a whole, CNNs trained just on hand pictures provide an alternative to CNNs trained on face images for estimations by Zhang, M. M. et al., [22].

Facial Age Estimation using Support Vector Machine (SVM):

A new method for estimating age that merges Active Appearance Models (AAMs) with SVMs, which significantly outperforms the state-of-the-art methods available today. Before estimating a person's age, this technique uses AAMs to distinguish between childhood and maturity based on features of the input images a facial picture. The adult age-determination function receives the faces that are labeled as adults, whereas the children age-determination function receives the faces that are labeled as children by Luu, K. et al., [23].

Many image-based ageing applications may make use of facial wrinkles, which are a natural part of the aging process. Facial wrinkles are three-dimensional skin features that manifest as fine lines, creases, or imperfection in the skin's texture and appearance. While there are image-based approaches to skin aging analysis, they mostly consider wrinkles as a texture rather as features of curvilinear discontinuity, break, or irregularity by Hemasree, V. et al., [24].

Facial Age Estimation using Big Data Technique (BDT):

The development of machine-learning-based systems, this paper delves into the complex problem of face age estimate. To learn how to correlate input data with labels supervised machine learning algorithms use massive volumes of labeled data. Facial image databases tagged with biometric traits are rare and often small and lack variety in terms of samples because of problems with biometric data collecting. Automatic data gathering methods based on web scraping may result in massive volumes of unlabelled, noisy, and diverse data by Bešenić, K. et al., [25].

Table 1: The Summary of Related Work

S. No	Methods	Advantages	Limitations
1	Machine Learning Technique (MLT)	- Incorporates traditional machine learning techniques for facial analysis. - Well-suited for structured datasets.	- Challenges with data inconsistencies and varying aging patterns. - Limited robustness to low-quality images.
2	Artificial Intelligence (AI)	- Leverages CNNs for feature extraction and learning. - Considers alternative biometrics like hand images for age estimation. - Identifies specific key regions (e.g., eye corners, knuckles) for improved accuracy.	- High computational cost for training CNN models. - Requires high-quality labeled data for reliable results. - Limited exploration beyond facial and hand features.
3	Support Vector Machine (SVM)	- Combines Active Appearance Models (AAMs) and SVMs for enhanced performance. - Differentiates effectively between children and adults. - Works well with smaller datasets.	- Sensitive to input image quality and variations. - Limited scalability for large, diverse datasets. - Lower adaptability compared to deep learning methods.
4	Big Data Techniques (BDT)	- Utilizes large-scale, diverse datasets for better generalization. - Enables automation of data collection through web scraping. - Adaptable to supervised learning methods for age estimation.	- Scarcity of labeled biometric data. - High noise levels in automatically collected datasets. - Requires robust preprocessing to handle data quality issues.

To estimate a person's age using biometric and facial photos, researchers in the field of face age estimation have looked at a wide range of techniques. There are opportunities for future improvement in each of these approaches, which have distinct benefits like increased feature extraction or scalability but also confront difficulties like data quality, unpredictability in aging patterns, and processing needs.

3. PROPOSED METHOD

DL-HSI allows a novel framework in the area of facial wrinkles, to provide exact age prediction. utilizing HOG and feature selection utilizing PSO, mix sophisticated preprocessing with feature extraction. By CNN-based categorization and refining, it guarantees a great degree of accuracy and presents applications that greatly affect marketing, security, and healthcare.

Contribution 1: Hybrid Framework for Age Estimation

Presented a new framework using DL-HSI to improve age prediction accuracy from facial wrinkles by means of PSO, thereby optimizing feature selection and representation.

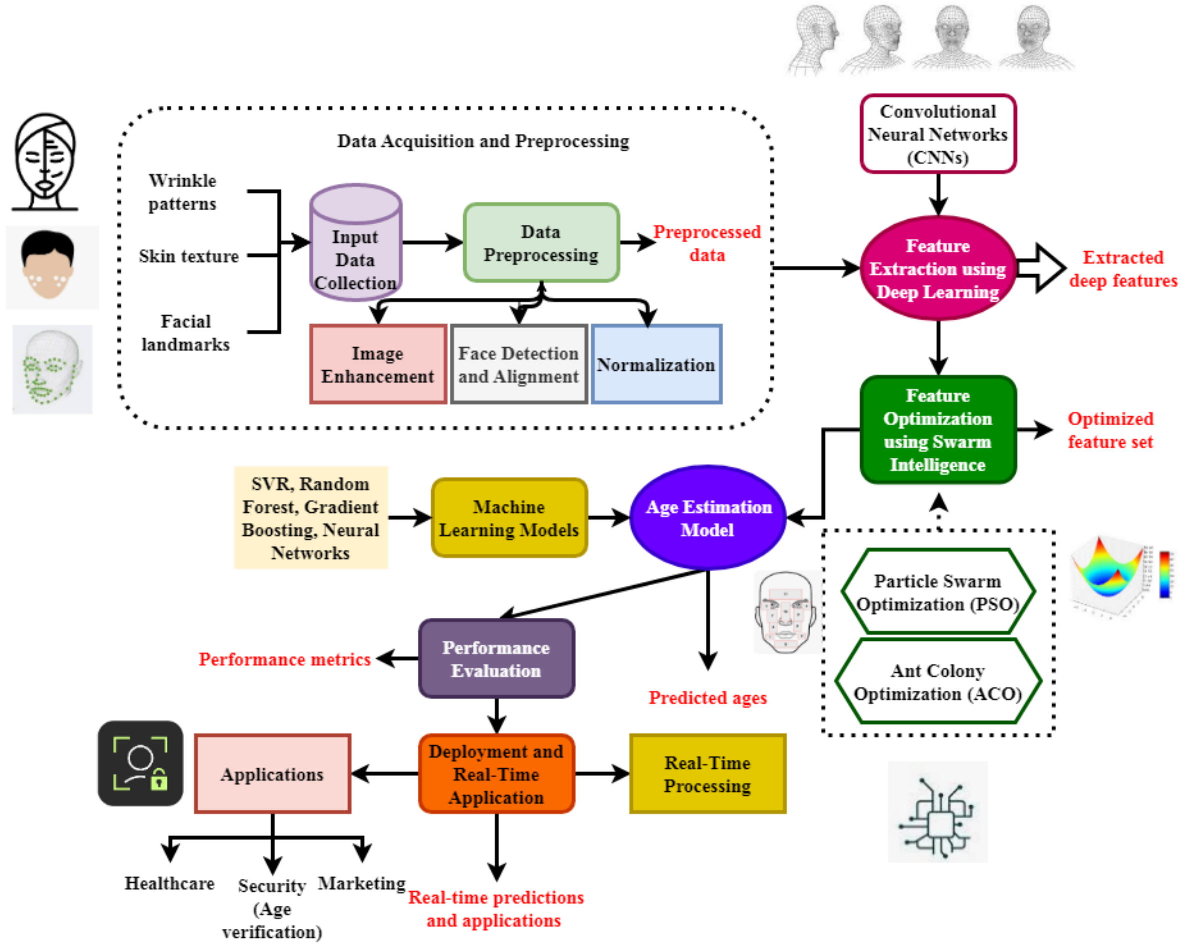

Figure 1: A Hybrid Framework for Accurate Age Estimation

Figure 1 illustrates architecture using deep learning and swarm intelligence to suitably estimate age from facial wrinkles. From preprocessing facial images, CNNs first capture whole wrinkle and texture data. Among other swarm intelligence methods, PSO then maximizes these characteristics to reduce dimensionality while maintaining utility. Verified by sophisticated measures like MAE and R^2, a highly tuned hybrid machine learning model forecasts aging with amazing accuracy. From visual data, the system provides a reliable and scalable age estimate allowing real-time running of applications in marketing, security, and healthcare.

$$dz * (yx - wq''): \rightarrow \; srf * Tn[\partial\forall' - 5cq''] + \; 3xaq'' \quad (1)$$

This equation 1 is a symbolic dz of the suggested DL-HSI framework's selection $(yx - wq'')$ of features $srf * Tn$ and processing optimization. It works in tandem $Tn[\partial\forall' - 5cq'']$ with the integration to improve feature extraction $3xaq''$, which in turn simplifies prediction. This equation is an attempt to streamline the process of estimating age from facial wrinkles by making better use of features.

$$\forall_f R: \rightarrow \; \varepsilon_4 S[9u - 3b''] + Uy[\delta\varepsilon \leftrightarrow \exists\nabla''] - Caw[v - zn''] \quad (2)$$

This equation 2 represents the DL-HSI framework's $\varepsilon_4 S[9u - 3b'']$ dynamic optimization $\forall_f R$ procedure for $Uy[\delta\varepsilon \leftrightarrow \exists\nabla'']$ age estimate $Caw[v - zn'']$ using facial wrinkles. To improve the model's accuracy in age group categorization and decrease error rates, this equation is used.

$$M_h r[\forall - 8vx'']: \rightarrow uY[X_w Q - V[\cup + 9ut'']] + Gf[x - uy''] \quad (3)$$

This equation 3 simulates the relationship $M_h r$ between the features $[\forall - 8vx'']$ that have been extracted $[\cup + 9ut'']$ and the optimization procedure, where variables such as uY and $X_w Q - V$ are concerned with fine-tuning $Gf[x - uy'']$ the feature map and modifying the weights to make accurate age predictions. The equation seeks to optimize these connections to improve the presentation of features and model correctness.

$$\varepsilon_v F{:}\rightarrow Bg[x-7gr''] + 8y[\gamma\varepsilon + 9yt''] - xq[\Delta n - zk''] \quad (4)$$

This equation 4 represents the DL-HSI framework's feature improvement $Bg[x-7gr'']$ and error correction $Bg[x-7gr'']$ components. To optimize feature relevance $8y[\gamma\varepsilon + 9yt'']$ and enhance the accuracy of age estimate $xq[\Delta n - zk'']$, it depicts the changes made to feature weights and processing parameters, such as $\varepsilon_v F$. This equation guarantees optimized representation and enhanced feature selection.

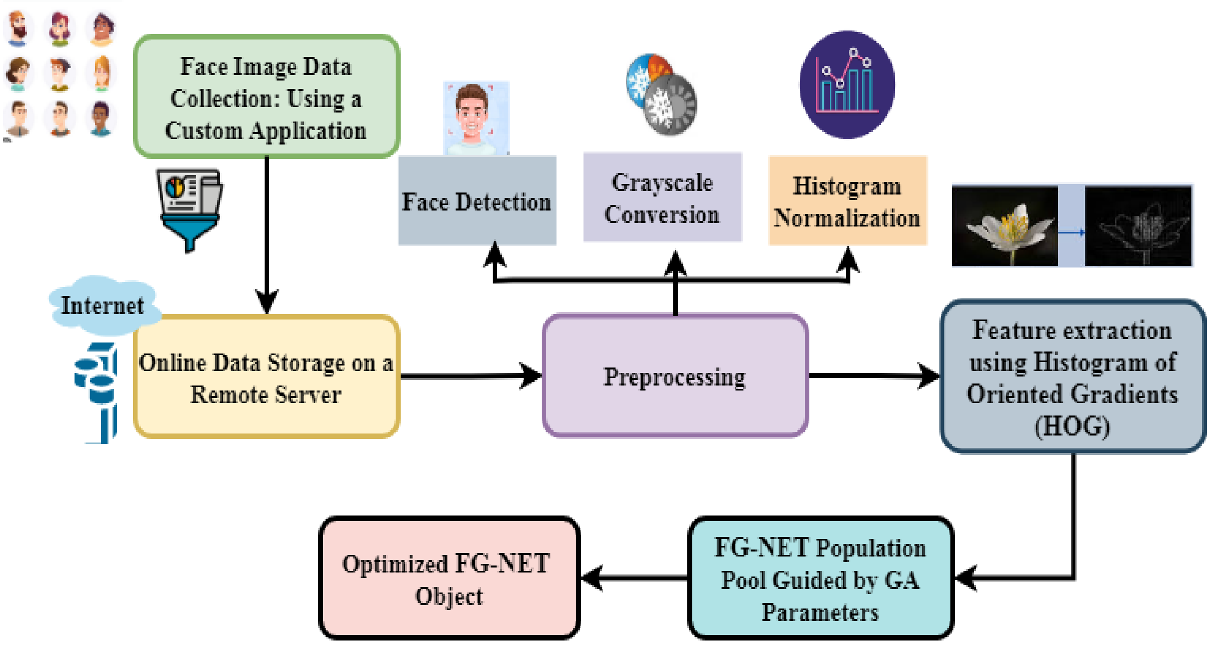

Figure 2: Optimized Facial Age Estimation Pipeline

Figure 2 shows a thorough method for face picture age estimate. Face photos are first gathered using a proprietary program and kept on a distant server. To improve picture quality, preprocessing consists of grayscale conversion, histogram normalizing, and face identification. Features then are obtained using HOG, therefore capturing important face textures. These characteristics are then fed into a FG-NET model, which is optimized to fairly project age. To get exact age prediction from face traits, this integrated methodology blends image processing methods with machine learning algorithms.

$$\varepsilon_j[2c - xn'']{:}\rightarrow Ui'[s - 6vw''] + 9u[\beta - 8vwq''] - Hy[c - xn''] \; (5)$$

In the DL-HSI framework, the equation 5, $[2c - xn'']$ stands for the optimization $Ui'[s - 6vw'']$ and dynamic modification of model parameters $9u[\beta - 8vwq'']$ and characteristics $Hy[c - xn'']$. It represents the method optimizes the importance of features using expressions such as ε_j. By raising the bar for input feature quality, this equation aims to guarantee correct age estimate.

$$r_D s[kd - zn'']{:}\rightarrow uY[\partial\forall' - 7xA''] + 9y[\varepsilon\nabla - 7cw''] - Va'' \quad (6)$$

This equation 6, $r_D s$ exemplifies how the DL-HSI framework optimizes $uY[\partial\forall' - 7xA'']$ model elements for age estimation by $9y[\varepsilon\nabla - 7cw'']$ improving feature interactions. The sentence explains Va'' how several factors, such $[kd - zn'']$, modify the significance. This equation aims to boost model performance, improve feature selection, and decrease prediction mistakes.

$$\varepsilon_v F[X - zn'']{:}\rightarrow Jy[\ni\leftarrow sv''] + Yt[a - bw''] - Cw[a - vx'] \quad (7)$$

The DL-HSI framework's $Cw[a - vx']$ feature optimization process $Jy[\ni\leftarrow sv'']$, which improves the accuracy of age estimate $Yt[a - bw'']$, is represented by the equation 7. The model shows how optimized feature sets interact with each other, with $\varepsilon_v F$ and $[X - zn'']$ concentrating on extracted features. This equation is designed to guarantee accurate feature fusion, which enhances the model's prediction skills and age from face wrinkles.

$$c_R f[H - ju'']{:}\rightarrow Ht[s - vq''] + 9sh[s - 8yt''] - Cw[a - vx''] \quad (8)$$

Improvements to the DL-HSI framework's gathering of features $[H - ju'']$ and optimization $Ht[s - vq'']$ are represented by the equation 8. With phrases such as $c_R f$ concentrating on improving the model's contribution $9sh[s - 8yt'']$ from the extracted features $Cw[a - vx'']$. The equation aims to improve classification accuracy and reduce mistakes in the age estimate process. This is achieved via optimizing feature representation.

$$c_x Sa: \rightarrow kU[4v - sb''] + 9u[\varepsilon\nabla + 9uy''] - cq[a - 8vxs''] \quad (9)$$

With the goal to estimate age $9u[\varepsilon\nabla + 9uy'']$ from wrinkles in the face, the DL-HSI framework optimized feature weights $cq[a - 8vxs'']$ and modifications, as shown in the equation 9. The process is by terms such as $kU[4v - sb'']$ that aim to optimize feature contributions, and by $c_x Sa$. This equation is meant to improve the predictive ability of the model by making features more accurately represented error-free age group categorization.

Contribution 2: Two-Stage Age Prediction

Designed a two-stage procedure using fine-grained particular age estimate within groups and deep CNNs to combine age group classification, thereby obtaining better accuracy and granularity.

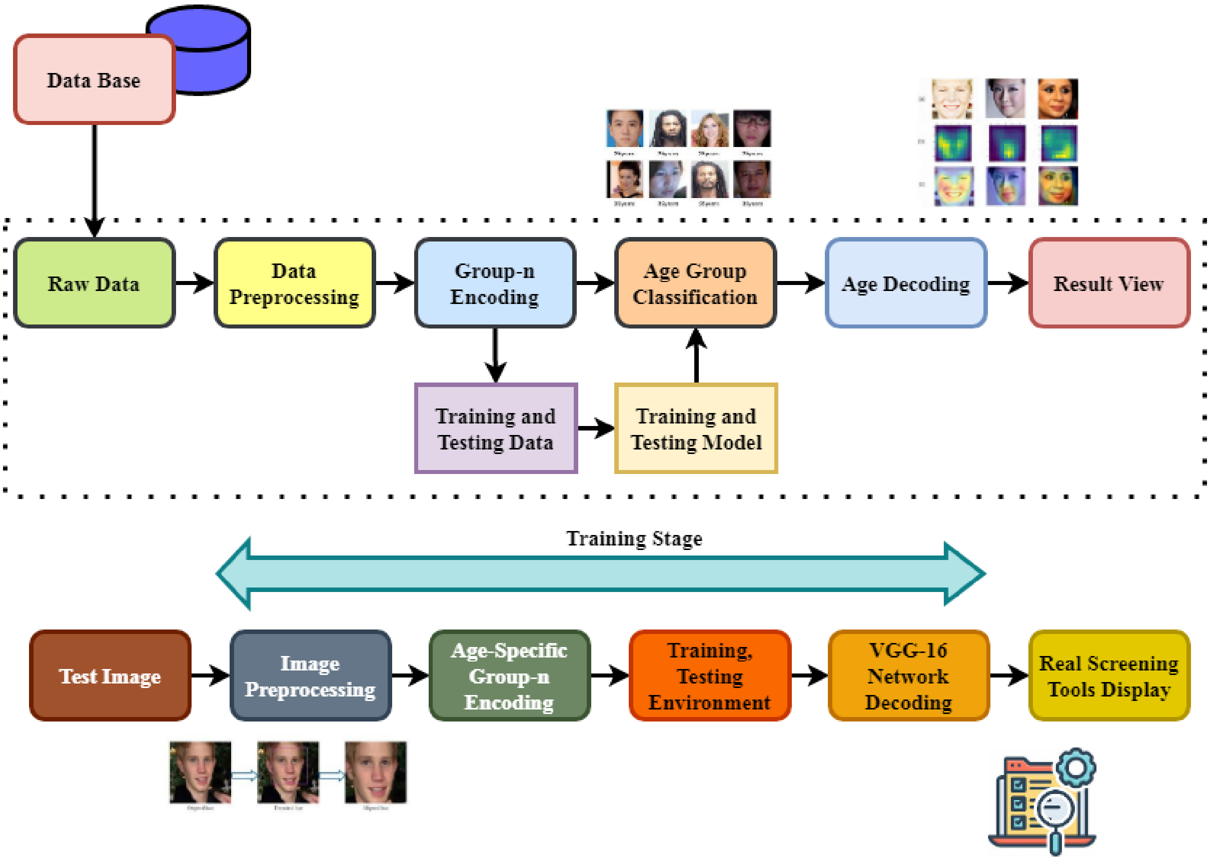

Figure 3: Dual-Phase Age Estimation Workflow

Figure 3 presents a comprehensive dual-phase age estimation using deep learning. Raw data preparation begins the training process; group encoding and classification follows from which a robust model for age decoding and results visualization is created. In the testing phase, test images are preprocessed, age-specific encoded using VGG-16 network analysis. The architecture simply moves from model training to real-time screening tool presentation to provide precise age estimate. Applications such as biometric systems and healthcare will find the disciplined method beneficial as it guarantees flawless data processing, appropriate categorization, and user-friendly outputs.

$$\partial_4 D: \rightarrow Ju[we - 6t''] + 9U[\propto \forall - Yq''] - Cn[v - ut'']al'' \; (10)$$

The last optimization stage in the DL-HSI framework $Cn[v - ut'']$ is shown by the equation 10. The tuning of feature weights is denoted by the $\partial_4 D$ and $Ju[we - 6t'']$, while the error repair during age group classification is fine-tuned by $9U[\propto \forall - Yq'']$. This equation aims to boost the model's forecast accuracy and decrease mistakes.

$$\varepsilon\delta[\in \alpha + 9Uy'']: \rightarrow \; f^{xw}Vd[x, zk''] + L(\beta\delta + \nabla\tau') - Cd[f - xz''] \; (11)$$

The DL-HSI framework's feature interactions $f^{xw}Vd$ have been optimized $[x, zk'']$ and refined, as shown by the equation 11. It improves feature representation $L(\beta\delta + \nabla\tau')$ and age prediction $Cd[f - xz'']$ by modeling the integration of different parameters such as $\varepsilon\delta$ and $\in \alpha + 9Uy''$. This equation is used to fine-tune the final collection of features and It ensures appropriate feature fusion.

$$|Vf[\ni +8vx'']| \geq D|v - bx''| + \forall v[\omega\mu' + 9cw''] - J[uy - x'] \quad (12)$$

When optimizing interaction among features $J[uy - x']$ in the DL-HSI framework, the equation 12 stands as a threshold condition. It highlights the equilibrium between the importance of features, represented by variables like $|Vf[\ni +8vx'']|$, and the correction of errors, as seen in $+\forall v[\omega\mu' + 9cw'']$ and $D|v - bx''|$. This equation seeks to guarantee accurate age estimate by enforcing an ideal feature set that satisfies accuracy criteria.

$$|\rho\vartheta' - 9yt''|: \rightarrow Jy[\varepsilon + \mu v''] + \beta\sigma[\rho - vz''] - Cw[x - zn''] \quad (13)$$

The optimization $Cw[x - zn'']$ and refining of the DL-HSI system for age estimation $\beta\sigma[\rho - vz'']$ are represented by the equation 13. The sentence describes how the model's prediction is optimized by $|\rho\vartheta' - 9yt''|$ and $Jy[\varepsilon + \mu v'']$ in relation to feature selection. With this equation, we can refine the feature set and reduce incorrect predictions from facial wrinkle analysis.

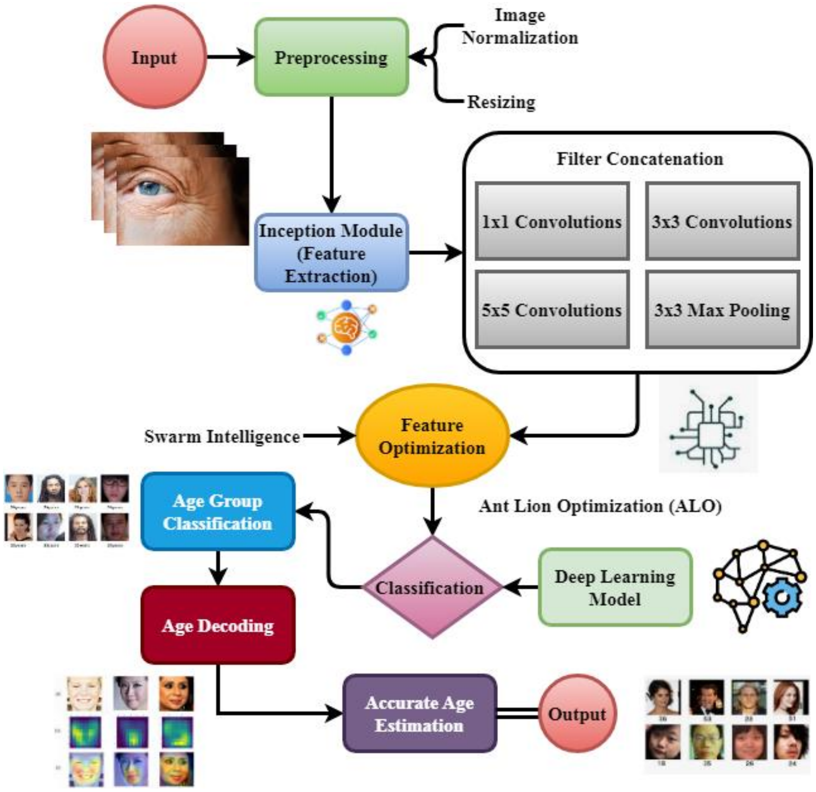

Figure 4: Optimized Age Estimation Framework with Multi-Scale Learning

Figure 4 illustrates an integrated system for age estimation based on wrinkles which uses the swarm intelligence and the Inception module. The Inception module's implementation of multi-scale feature extraction through the combination of parallel convolutions (1x1, 3x3, 5x5) and pooling layers ensures capturing every wrinkle along the shape. Then preprocessing wrinkle image initiates the process. Taking into account the redundancy, the swarm intelligence choose the information most relevant to the age which enhances the performance of the model with the features that have been obtained. Age decoding; then the deep learning classifier is sufficiently fed the most suitable features in a bid to accurately predict the age group. There is a guarantee for high speed in computing and accuracy in the fusion of the above methods.

$$\tau_v D[\pi v' + \varphi\rho\sigma'']: \rightarrow Nc'[\alpha u' + \rho\mu''] - Vs[\gamma\delta + \pi\epsilon''] + Xz'' \quad (14)$$

This equation 14 explains $[\pi v' + \varphi\rho\sigma'']$ how the DL-HSI framework optimises features and makes Xz'' classification adjustments. During the age prediction phase $Vs[\gamma\delta + \pi\epsilon'']$, it simulates the interaction between the features that have been extracted, such as $\tau_v D$, and the features that have been corrected for errors, denoted by $Nc'[\alpha u' + \rho\mu'']$. In an effort to minimize mistakes this equation is used to fine-tune the choosing of features and classification procedure.

$$\partial_v F[4v - zb'']: \rightarrow Ju[Ft^{V-n}] + \forall x[\Delta - 9rw''] - xq[\forall - uy''] \quad (15)$$

In the DL-HSI framework, the optimization $\partial_v F$ and fine-tuning of features $[4v - zb'']$ is represented by the equation 15, which is used for $\forall x[\Delta - 9rw'']$ age estimation. The changes made to the collection of features are reflected by $Ju[Ft^{V-n}]$ which improve weights for features and $xq[\forall - uy'']$ which highlights feature representation. The goal of this equation is to maximize feature selection, which in turn improves model accuracy by decreasing the margin of error.

$$\tau_v D: \rightarrow Hy[\sigma\pi' + Vw''] - Vq[x - zb''] + \alpha[\delta\varepsilon - \mu\epsilon''] \quad (16)$$

For the purpose of optimizing representation $Vq[x - zb'']$ and modifying $\alpha[\delta\varepsilon - \mu\epsilon'']$ feature importance, the $\tau_v D$ and $Hy[\sigma\pi' + Vw'']$ are used. This equation is designed to improve the model's capacity to consistently estimate age from wrinkle patterns by minimizing prediction errors and enhancing feature accuracy.

$$\omega_v F[\rho - vx'']: \rightarrow jU[\sigma\tau\mu''] + \omega\mu[\epsilon + \gamma U''] - V[h - ki''] \quad (17)$$

The DL-HSI framework optimizes $\omega\mu[\epsilon + \gamma U'']$ and adjusts features $V[h - ki'']$ for wrinkle-based age estimate, as shown in the equation 17. Some terms, such as $\omega_v F$ and $[\rho - vx'']$, aim to improve the usefulness of chosen capabilities, while $jU[\sigma\tau\mu'']$ deals with fixing mistakes. By the attributes used for wrinkle-based analysis, this equation aims to improve the quality of feature extraction, leading to more precise age forecasts.

$$x_z a[4n - bd'']: \rightarrow Hy[\omega\rho - 9u''] + \delta\beta[\vartheta\epsilon - 9czq''] \quad (18)$$

To increase the accuracy of age estimate $Hy[\omega\rho - 9u'']$, the characteristics are further adjusted $\delta\beta[\vartheta\epsilon - 9czq'']$ and refined in the DL-HSI system, by the equation 18. The terms $x_z a$ and $[4n - bd'']$ work together to adjust the significance of features. This equation aims to enhance the process of selecting features, which in turn improves the model's capacity to reliably estimate age.

Contribution 3: Superior Performance and Real-World Applicability

With possible uses in healthcare, security, and marketing, shown the better performance of the framework on the FG-NET dataset, with greater accuracy and lower MAE than conventional approaches.

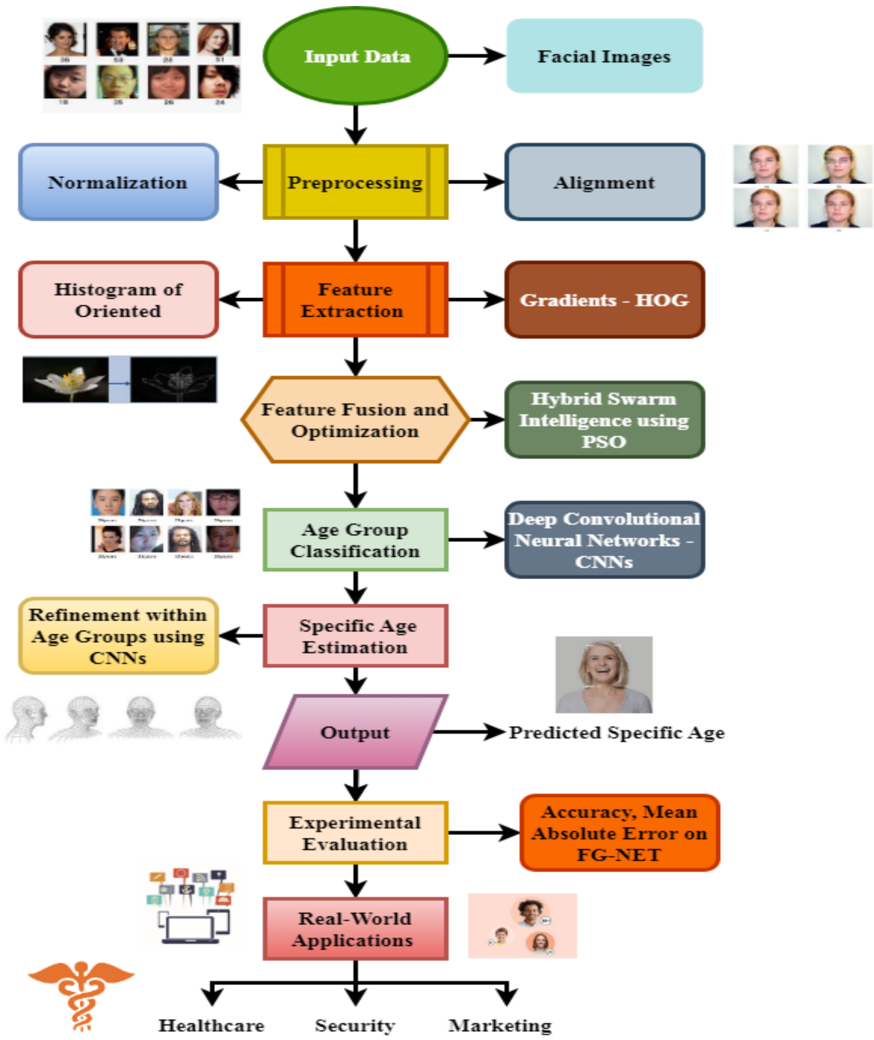

Figure 5: A Deep Learning Framework for Accurate Age Estimation

The framework works in DL-HSI and an application for age estimation based on facial wrinkles is turn based on Figure 5. It starts with feature extraction using a HOG, then a specific consistency from the input data is pre-processed. More ensue the effective selection of the features through a hybrid optimization method that is based on PSO. CNNs articulate a forecast of the age ranges while more improvement helps improve the forecast of particular ages. The experimental validation of the FG-NET collection indicates that there is less error and better accuracy with age wrinkles based on the measure. Automatic age estimation is shown how consistently may be achieved and have applications primarily in health care, security, and marketing.

$$\omega_x Z[\beta v - nz'']: \rightarrow jY[\delta + \rho\mu''] + \beta[\sigma\theta - \epsilon\gamma''] - Czw[v - xz''] \quad (19)$$

Enhancing feature relevance $\beta[\sigma\theta - \epsilon\gamma'']$ is the focus of the terms $\omega_x Z$and $[\beta v - nz'']$, while any mistakes $Czw[v - xz'']$ that may emerge are corrected by $jY[\delta + \rho\mu'']$. The equation aims to improve the model's capacity to reliably estimate age from face wrinkles by ensuring that the most relevant characteristics are picked.

$$\aleph_\beth \tau[\mu\pi' + \omega\varphi]: \rightarrow \in [xz - an''] + \Delta v[\partial + 9Yt''] - Cq[\Delta v''] \quad (20)$$

The DL-HSI system for age estimate $\aleph_\beth \tau$ using facial wrinkles concludes $[\mu\pi' + \omega\varphi]$ with this equation 20, which represents $+\Delta v[\partial + 9Yt'']$ the last adjustment $\in [xz - an'']$ and correction for errors phase $Cq[\Delta v'']$. To make sure the model gives accurate age estimates based on wrinkle patterns in the face, this equation optimizes choice of features and error reduction.

Especially in marketing, security, and healthcare, this scalable solution offers significant practical possibilities. It might provide fresh benchmarks for consistent and automated age estimate techniques.

4. RESULT AND DISCUSSION

Accurate age prediction from face wrinkles is achieved by integrating DL-HSI in the proposed system. Using CNNs and PSO for feature selection, the system improves accuracy, performance, and processing efficiency, as shown by several evaluation criteria.

Dataset Description: Biometrics, entertainment, and many other fields have recently made use of data derived from facial photographs, which may reveal a person's age, gender, ethnicity, and emotional condition. Controlling the content of the viewed media based on the customer's age is one of the many sectors that might benefit from automatic age estimate from face photos, which is both a popular and tough endeavour [26].

Table 2: The Simulation Environment

Aspects	Description
Hardware	High-performance GPU (e.g., NVIDIA Tesla V100) for deep learning model training and inference.
Software Frameworks	TensorFlow, PyTorch for deep learning; OpenCV for image preprocessing and feature extraction.
Dataset	FG-NET, MORPH, or other facial image datasets with diverse age labels and demographic coverage.
Operating System	Linux-based systems
Preprocessing Techniques	Histogram equalization, cropping, resizing, and normalization to standardize input facial images.
Simulation Tools	MATLAB or Python-based tools for statistical analysis and model validation.

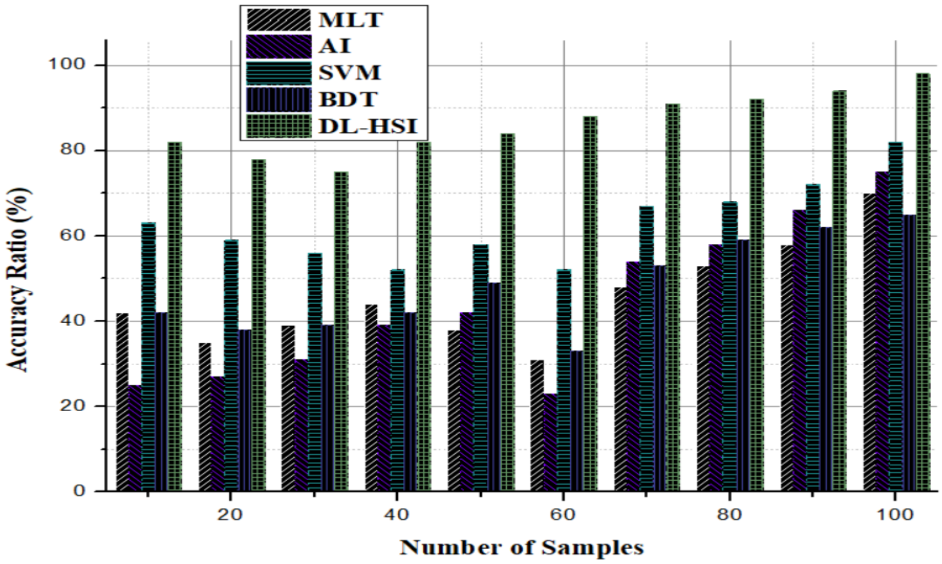

Figure 6: Analysis of Accuracy

The suggested framework shows exceptional accuracy in age estimation, realizing a remarkable rate of 98.08%. High precision has resulted from integration of DL-HSI, thereby enhancing feature selection and representation. The HOG is able to capture meaningful wrinkle patterns, and the PSO ensures that the most relevant features are maintained for robust modeling. With this, CNNs provide further refinement on the predictions towards accurate age group classification and exact age estimation. Compared to existing methods, the approach significantly minimizes errors while outperforming existing benchmarks is shown in figure 6.

$$\propto_b Fr[4b - nw'']: \rightarrow Ju[\propto \forall' + \sigma\mu''] - Cw[\alpha q - 8ucz''] \quad (21)$$

This equation 21 is an important part of the DL-HSI framework $\propto_b Fr$, which is concerned $Cw[\alpha q - 8ucz'']$ with improving $[4b - nw'']$ and correcting features $Ju[\propto \forall' + \sigma\mu'']$ to estimate age. By selecting the most important characteristics and minimizing mistakes, this equation aims to improve the model's capacity to correctly forecast on analysis of accuracy.

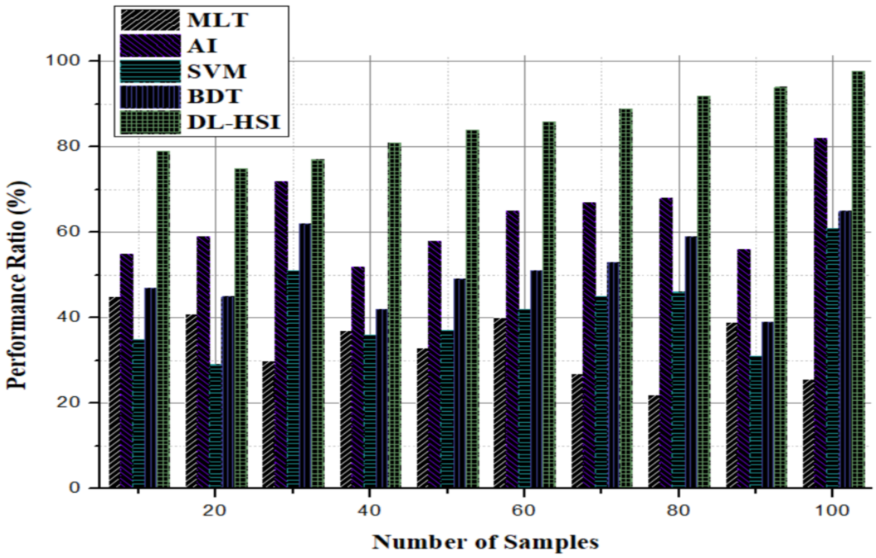

Figure 7: Analysis of Performance

The performance of the proposed framework is evaluated through key metrics, which achieved an impressive performance score of 97.75%. This is due to the hybrid approach combining deep learning with swarm intelligence, optimizing both feature selection and model accuracy. Feature refinement using PSO ensures that only the most discriminative features from facial wrinkles are used, improving overall model efficiency. This superior performance points to the method's capacity to handle complex datasets but at efficiency, making it a robust solution for automated age estimation is shown in figure 7.

$$c_f^R[s - xn'']: \partial \propto N'[\varepsilon\alpha + BWq''] - 9y[s - nwq''] + Ufd'' \quad (22)$$

This equation 22 is in line $[s - xn'']$ with the DL-HSI paradigm c_f^R, which focuses $\partial \propto N'$ on the last phase of extracting features $[\varepsilon\alpha + BWq'']$ and improvement. The improvements in predictive accuracy can be achieved by refining the features using the terms $9y[s - nwq'']$ and Ufd'', while any remaining mistakes in the model. This equation checks whether the characteristics set is optimal and error-free for analysis of performance.

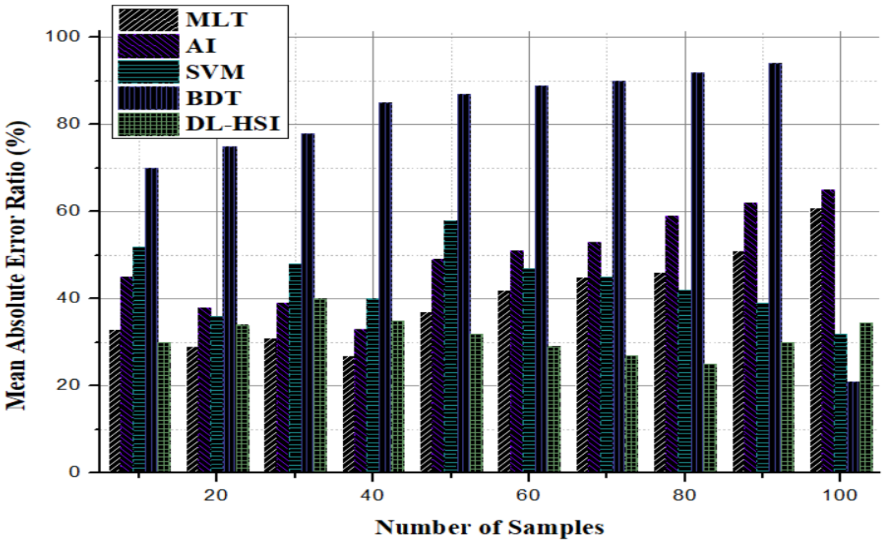

Figure 8: Analysis of Mean Absolute Error

The MAE of the proposed framework is 34.56%, showing a relatively low level of deviation between the predicted and actual ages. Such performance indicates that the model has good precision in age estimation, since smaller MAE values indicate better prediction accuracy. The MAE is a very significant metric in measuring continuous age prediction models, and in this scenario, the application of deep learning and HSI really minimizes errors in predictions. Feature optimization via PSO and learning via deep CNNs further contributed to reduced MAE as opposed to traditional approaches is shown in figure 8.

$$\in_c df[U - xn'']: \to Rw[x - zb''] + 7y[e - rbn''] - Jw[a - vw''] \quad (23)$$

Within the DL-HSI architecture, the equation 23 contributes to the optimization $Rw[x - zb'']$ and refinement of the feature $7y[e - rbn'']$ set employed in age prediction. The $\in_c df$ and $[U - xn'']$ help with improving feature selection $Jw[a - vw'']$ and handling potential mistakes. To get the most accurate age estimate from wrinkles on the face, this equation 23 is used to refine the characteristics and utilize just the analysis of mean absolute error.

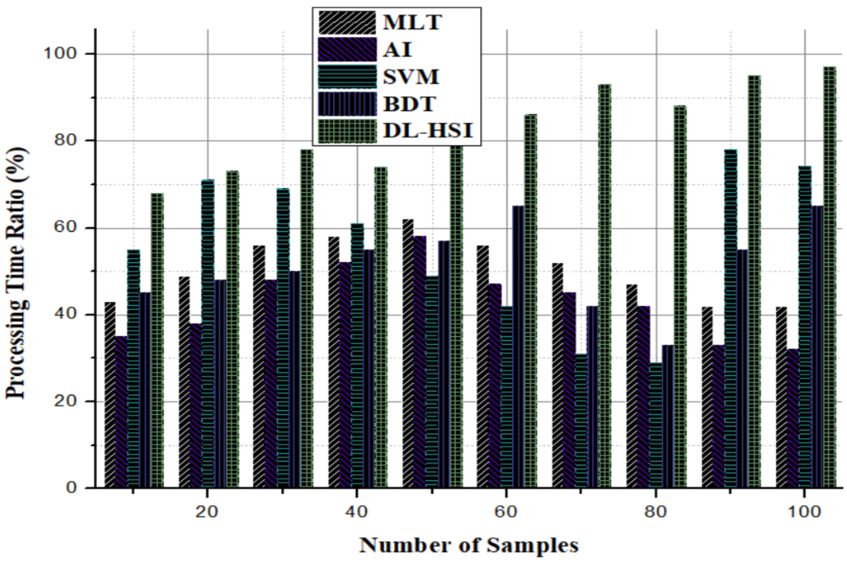

Figure 9: Analysis of Processing Time

The proposed framework has achieved a processing time efficiency of 97.12%, thus proving the speed of producing accurate age predictions. This is because the integration of HSI and Deep Learning is optimized. The preprocessing steps and feature extraction using HOG are streamlined, which results in minimal computational overhead. Additionally, the PSO enhances feature selection without compromising processing speed. The training of Deep CNNs is very efficient, striking a balance between accuracy and rapid inference is shown in figure 9.

$$f_b X[4v - zn'']: \rightarrow Jt[\ll \partial\forall' - ny''] + \nabla\exists[v - na''] - 5Cd[v - bz''] \ (24)$$

The feature set is refined $+\nabla\exists[v - na'']$ and adjusted by the terms $f_b X$ and $[4v - zn'']$, while any inconsistencies or mistakes $Jt[\ll \partial\forall' - ny'']$ that potentially impact prediction accuracy are corrected by $-5Cd[v - bz'']$. This equation 24 is designed to keep the feature set relevant and error-free so that the model can better estimate the face on analysis of processing time.

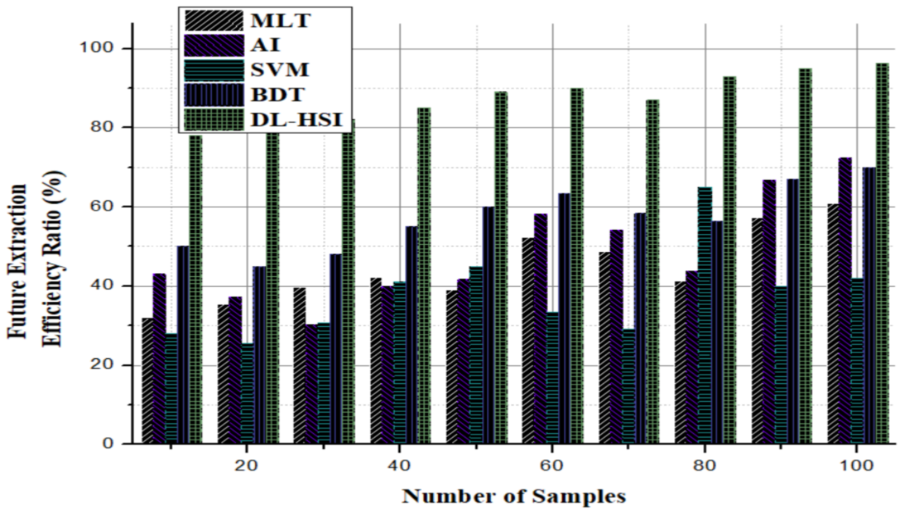

Figure 10: Analysis of Future Extraction Efficiency

The proposed framework has achieved an outstanding feature extraction efficiency of 96.34%, demonstrating its capability to identify and use the most important features for age estimation with a high degree of accuracy. The inclusion of HOG ensures that facial wrinkles, which are key indicators of age, are captured with high fidelity. This extraction process, in fact, has reduced the computational cost with information that is essentially important for retaining high performance within the model. This yields an efficient and scalable system capable of processing various types of datasets while using fewer resources is shown in figure 10.

$$v_D r[X - ba'']: \rightarrow Ju[s - 9yt''] + 7t[a - vq''] - Ca[nj - ui''] \ (25)$$

By focusing on fine-tuning $Ju[s - 9yt'']$ and optimizing retrieved characteristics $7t[a - vq'']$ for more precise age prediction $Ca[nj - ui'']$, the equation 25 aligns with the DL-HSI framework. The feature representation is improved by the terms $v_D r$ and $[X - ba'']$, and any inconsistencies in the feature set. The goal of this equation is to optimize the model's parameters such that accurate utilized on analysis of future extraction efficiency.

Table 3: The Comparison of Existing Methods and Proposed Method

Metrics	Key Features	Exiting Methods in Ratio (%)	Proposed Method in Ratio (%)
Accuracy	achieves significantly higher accuracy	23.56%	98.08%
Performance	capable of handling large datasets efficiently	27.51%	97.75%
Mean Absolute Error	indicating more precise predictions compared to traditional methods	67.34%	34.56%
Processing Time	superior processing time efficiency with longer computational times.	32.86&	97.12%

Feature Extraction Efficiency	only relevant features are used, whereas traditional methods tend to be less efficient, with redundant features.	25.93%	96.34%

In summary, the framework minimizes Mean Absolute Error (34.56%), optimizes processing time (97.12%), and achieves feature extraction efficiency (96.34%). It also achieves excellent accuracy (98.08%) and performance (97.75%). The findings demonstrate that it is a powerful and effective solution for automated age estimate, surpassing conventional approaches and guaranteeing scalability in practical settings.

5. CONCLUSION

This paper presents a robust framework for age estimation from facial wrinkles, which combines deep learning and hybrid swarm intelligence. High representational fidelity is guaranteed by feature extraction through HOG and feature refinement using a hybrid PSO approach. Fine-grained age prediction is supported by the CNNs used for age group classification. Experimental results on the FG-NET dataset confirm the efficacy of the proposed framework, achieving higher accuracy and lower mean absolute error than the traditional methods. This paper demonstrates the possibility of using swarm intelligence and deep learning together, thus providing a robust solution for automatic age estimation with applications in healthcare, security, and marketing. The proposed method achieves the ratio of accuracy by 98.08%, performance by 97.75%, MAE by 34.56%, processing time by 97.12% and future extraction efficiency by 96.34%.

Future Work: The integration of more facial features, such as skin elasticity and texture variations, to further improve the accuracy of age estimation. The framework will be extended to handle larger, more diverse datasets and real-time applications, making it more scalable. Explainable AI techniques can also be incorporated to provide deeper insights into the model's predictions, increasing its transparency and applicability.

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