# ORPHAN BABY ADOPTION SYSTEM BASED ON PARENT CHILD FACIAL FEATURES

**Badisa Pranava Sai**
*Department of Artificial Intelligence & Data Science*
Parul University,
Gujarat, India
pranavasai051@gmail.com

**Mohdmaaz.shaikh**
*Department of Artificial Intelligence & Data Science*
Parul University,
Gujarat, India
maaznshaikh@gmail.com

***Abstract*— The number of digital forensic investigations involving indecent pictures of children (IIoC) has increased significantly, and one of the main obstacles investigators confront is the laborious process of manually searching images for illegal content. CAID (Child Abuse picture Database) is a standard national repository of IIoC that law enforcement in the UK maintains and utilizes to match picture hashes and information to identify known illicit photos. Faster and more efficient IIoC studies are made possible in large part by the CAID. However, human analysis is necessary for any photos that cannot be matched using CAID. Investigators must view each photograph and confirm that it is IIoC. The estimation of the victim's age in the photos—that is, whether they are an adult or juvenile, as this would alter the investigation's trajectory—is an essential step in this verification process, but it takes time because there are many photos to review, which slows down the investigation. Human investigators find this to be a difficult and time-consuming. Deep learning has the potential to accurately assess age in photos, as previous research has shown. This speeds up the inquiry by lowering the quantity of photos that must be manually processed. However, a comparative study utilizing the same datasets to determine the best deep learning model and classification technique to employ is lacking in terms of practical implementation in IIoC investigations. We have shown that binary classification is the most effective method for identifying photographs as either children or adults, achieving the highest accuracy depends on parent child facial matching.**

***Keywords*— *facial recognition- deep learning- orphan adoption- image processing- child facial matching- adoption system***

## I. Introduction

Adoption is one of the most humane and selfless acts that provides orphaned children with a loving home, offering them a chance at a better life. For potential adoptive parents, choosing to adopt can be both a rewarding and complex decision, influenced by various factors such as emotional readiness, cultural fit, and the desire to provide a stable environment for a child. The process typically involves a series of interviews, psychological assessments, legal procedures, and home visits, but one element that is often not given much attention is the emotional connection that develops between parents and children.

For centuries, human beings have been drawn to the idea of familial resemblance, where we tend to feel more connected to people who bear similarities to ourselves, even if those similarities are subtle. This phenomenon is rooted in evolutionary psychology, where humans instinctively prefer individuals who look like them because it often implies shared genetics and kinship. In the context of adoption, this concept of "visual kinship" plays an essential role in the bonding process. Children and parents who share similar facial features often form deeper emotional bonds more quickly because it fosters a sense of belonging and comfort.

The orphan baby adoption process faces many challenges, such as a large gap between adoptable children and waiting parents, lengthy and complex legal procedures, social stigma, and a strong preference for younger children, which leaves many children, especially older ones and those with special needs, without families. Matching children with adoptive parents who share similar features can offer psychological and social benefits, including greater attachment and a stronger sense of belonging. Historically, adoption agencies have practiced "selective placement" by matching children and parents based on physical traits to promote smoother integration. Today, advanced facial recognition technology offers a method to objectively and efficiently compare facial features, potentially improving the accuracy and fairness of adoption matches, but ethical, privacy, and emotional considerations must be addressed.

One novel and emerging approach is to leverage facial recognition and similarity analysis to assist in the matching process between orphans and potential adoptive parents. The project “Orphan Baby Adoption System Based on Parent-Child Facial Features” proposes a system that uses facial feature comparison algorithms to evaluate the visual similarity between a child's face and that of prospective parents, with the goal of creating more emotionally resonant matches. In recent years, the integration of technology—especially artificial intelligence (AI) and computer vision—has opened new possibilities in making the adoption process more empathetic, data-driven, and efficient.

## II. Related work

The integration of advanced artificial intelligence technologies has significantly influenced fields such as facial recognition, social welfare systems, and document processing, providing a foundation for modern child adoption platforms. This project builds upon three core areas of research: AI-powered facial age estimation, AI applications in social welfare and adoption systems, and Optical Character Recognition (OCR) for secure and intelligent data handling.

### 1. AI for Facial Age Estimation and Recognition

Recent advancements in facial analysis and age estimation have greatly enhanced the accuracy and efficiency of demographic profiling. Earlier approaches, such as those by Kwon and da Vitoria Lobo (1999) [12] and Horng et al. (2001) [13] , relied on distance ratios of facial features and wrinkle patterns to classify individuals into broad age categories. More sophisticated models, like AGES (Geng et al., 2007) [14] and manifold learning (Fu and Huang, 2008) [15], used subspace and regression-based approaches to model the ageing process over time.

With the introduction of deep learning, convolutional neural networks (CNNs) have become a powerful tool for age estimation. Techniques such as DEX (Rothe et al., 2018) [16] and DS13K (Anda et al., 2019) [17] demonstrated state-of-the-art performance by leveraging pre-trained CNN architectures like VGG and ResNet. More recent studies, including Vec2UAge (Anda et al., 2021) [19] introduced advanced feature extraction and attention-based mechanisms to improve accuracy, even on unconstrained and diverse datasets. These models highlight the effectiveness of deep learning for analyzing facial characteristics and estimating age groups, which is directly applicable to child adoption platforms for matching age and facial features between prospective parents and children.

### 2. AI in Social Welfare and Adoption Systems

The role of AI in social welfare has expanded rapidly in areas such as healthcare, resource allocation, and adoption. As noted by Karim and Islam (2024) [5], most existing adoption systems in developing countries focus primarily on administrative management and lack intelligent matching or healthcare integration features. Machine learning can improve adoption compatibility analysis by considering demographic and psychological factors.

Beyond matching, AI has proven effective in addressing broader welfare challenges, such as early health issue detection (Zhang et al., 2019) [30] and resource distribution optimization (Kumar et al., 2021) [31], which can be adapted for child welfare ecosystems. Ethical considerations such as fairness, transparency, and privacy remain critical. Techniques like LIME and SHAP (Ribeiro et al., 2016) [32] provide explainability for AI models, which is vital in sensitive domains like child adoption. These studies form the foundation for AdoptConnect's fairness-aware AI matching system, which prioritizes cultural, linguistic, personality, and facial compatibility while ensuring ethical and transparent decision-making.

### 3. OCR for Document Processing and Secure Data Handling

Optical Character Recognition (OCR) technologies have been widely adopted for automated document extraction and processing. Chigali et al. (2022) [22] introduced OCR-assisted translation systems to break language barriers, while Chamchong et al. (2021) [33] demonstrated effective text recognition using CNN and RNN architectures for complex scripts. Advanced approaches have combined multiple OCR engines (Gradinaru et al., 2020) [34] to enhance accuracy and robustness, and frameworks like Azure Form Recognizer (Soh et al., 2023) [35] show practical applications in secure identity data extraction.

For platforms like AdoptConnect, OCR plays a critical role in automating document verification, extracting data from adoption forms and identity proofs while maintaining data security and privacy. This reduces manual processing, improves operational efficiency, and strengthens the reliability of adoption workflows.

Building upon these existing research areas, **AdoptConnect** integrates:

- **AI-powered facial recognition and age estimation** for photo-based child-parent matching,
- **AI in social welfare systems** for cultural, personality, and regional compatibility scoring, and
- **OCR technology** for automated and secure document processing.

This fusion of techniques establishes a **holistic, ethical, and efficient AI-driven adoption platform** tailored to the Indian context, addressing the limitations of traditional adoption systems while leveraging state-of-the-art research in AI and computer vision.

## III. Proposed Methodology

Using several approaches for age estimate in digital forensic investigation, we have compared pretrained deep learning models on our built datasets in this study. Initially, the dataset is created by merging pictures from different publicly accessible datasets. All of the dataset's images are converted to the same size, pixels, which was determined to be the most suitable size based on the datasets utilized.

The diagram represents the process flow of an Orphan Baby Adoption System that uses multi-factor analysis to match children with potential adoptive parents. Here's a step-by-step explanation of the flow depicted in the diagram:

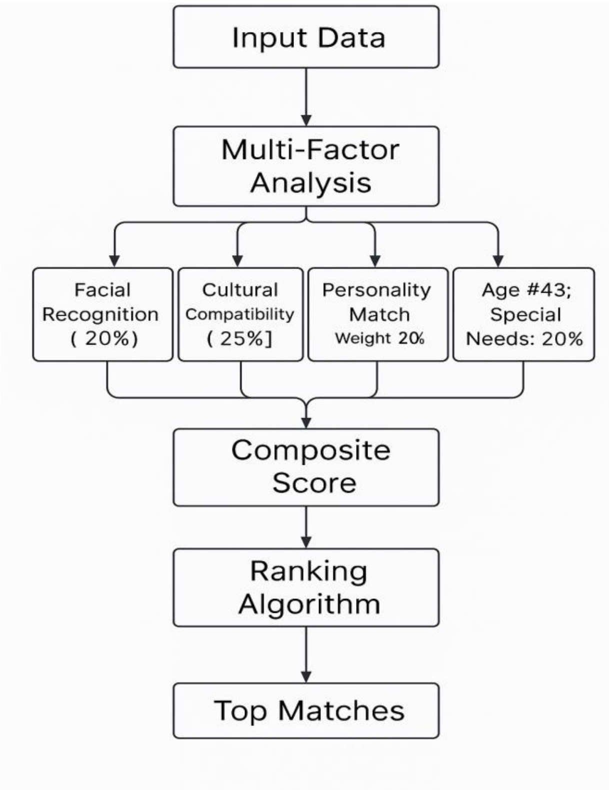


**Fig.1 Proposed methodology**

**Step 1: Input Data**

The process begins with the input data, which consists of several key pieces of information about both the orphan child and the adoptive parents. The data can include a variety of aspects like:

Facial features of the child and adoptive parents.

Cultural background information.

Personality traits of the adoptive parents.

Age of both the child and adoptive parents.

Special needs the child may have.

This data serves as the foundation for the system to generate matches.

**Step 2: Multi-Factor Analysis**

Once the input data is collected, it undergoes a multi-factor analysis. This step involves evaluating the data across several categories, each contributing a weighted percentage to the final analysis. The four primary categories under consideration are:

**Facial Recognition**

This category analyzes the facial features of the orphan child and the adoptive parents to identify physical resemblances. The system uses facial recognition algorithms to compare the features of the child and potential parents.

This step helps identify whether there are similarities between the faces of the parent(s) and the child, which may suggest a biologically-based emotional bond.

**Cultural Compatibility**

Cultural compatibility ensures that the orphan child and the potential adoptive parents are a good fit culturally. It includes factors like:

Shared language.

Cultural traditions.

Ethnic background.

This step assesses how well the adoptive parents' cultural values align with the needs and background of the child. Cultural compatibility is weighted heavily at 25% due to its importance in ensuring a smoother integration into the new family.

**Step 3: Composite Score**

After each of the factors has been evaluated, the system generates a composite score. This score is a weighted average of the four factors (facial recognition, cultural compatibility, personality match, and age/special needs). Each factor contributes its respective percentage to the overall score.

For example:

If a particular pair has a high match in cultural compatibility but a lower match in facial recognition, the weighted composite score reflects these discrepancies, ensuring that no single factor overpowers others unless it has more weight in the final decision (like cultural compatibility with 25%).

**Step 4: Ranking Algorithm**

Once the composite scores have been calculated, a ranking algorithm comes into play. This algorithm processes the composite scores and ranks the adoptive parents based on their total match score with the child. The ranking algorithm helps prioritize the best matches by considering the cumulative score, ensuring that the top matches are selected.

The ranking ensures that the highest-scoring parent-child pairings are prioritized for adoption.

**Step 5: Top Matches**

The system finally generates the top matches, which are the most compatible adoptive parents for the child. These matches will be based on the composite score derived from the multi-factor analysis. Adoption agencies can then review the top-ranked matches and proceed with the next steps of the adoption process, such as home visits, interviews, and background checks.

The top matches are essentially the final recommendations of the system, ensuring that the adoptive parents are the most emotionally and practically suitable for the child.

## IV. DATA ACQUISITION AND PREPARATION

In this work, a dataset has been constructed to contain images. The reason for constructing this dataset is to overcome the shortcomings identified through prior work. To understand the suitability of facial estimation techniques for digital forensic processes suspected of containing IIoC, it is necessary to have a representative and well-balanced dataset.

This entails collecting a sizable collection of photos from particular age groups. We have merged nine publicly accessible datasets to conduct a thorough assessment of the current deep learning models and get trustworthy results. A list of all datasets, the total number of photographs in each dataset, and the number of images of children (those under the age of eighteen) are shown in Table 1 and 2.

The following is a structured presentation of data sources and mock datasets, suitable for inclusion in the "Materials and Methods" section of a research paper on an orphan baby adoption system using parent-child facial matching. The datasets are described and organized for clarity and reproducibility.

A set of five detailed orphan child profiles was curated, reflecting diverse Indian names, locations, and cultural backgrounds. Each record includes demographic and physical attributes critical to the facial matching process.

**Table 1: Type of Storage**

| Type of Data | Description | Storage Method | Purpose |
|---|---|---|---|
| Mock Dataset | Pre-prepared fake/sample data | Stored in JSON files and static image folders | Fast local development, UI testing and demos |
| Real Dataset | Actual data collected from the real system | Stored in cloud services (AWS S3, Firebase Database) | Live production usage, scalability and secure storage |

**Table 2: Benchmark Dataset**

Table 2 presents the raw counts of total and child images across datasets, further analysis was conducted to better understand data balance, age distribution, and dataset weightage in the final training corpus.

| Dataset | Year | Total Images | Child Images | Labels Available | Domain Notes |
|---|---|---|---|---|---|
| AgeDB | 2017 | 16,488 | 317 | Age | Benchmark datasetfor age vertification |
| APPAREAL | 2018 | 7591 | 436 | Real&apparent age | Apparent age estimation |
| CACD2000 | 2014 | 1,63,446 | 2837 | Age,Id | Celebrity dataset |
| IFDB | 2015 | 780 | 780 | Age,Gender | Regional Indian Dataset |
| KANFace | 2021 | 40000 | 1515 | Age,EthnicityGender | High quality facial attributes |

The number of photos taken from each dataset that showed people younger than 18 is explained below.

- AgeDB is a "in-the-wild" collection with 16,488 photos, containing both adult and child photos (Moschoglou et al., 2017) [25]. Google Images is used manually for both image collecting and age determination. This dataset includes pictures of actors, scientists, and other people that are accessible to the general public. The subject photos were taken in an uncontrolled setting with various stances, noise levels, impediments, and expressions. There are 568 people in this dataset, ranging in age from 1 to 101 years, with around 29 photos of each subject. Only 317 of these photos were used, and in those cases, the subject's age was determined to be under 18.
- The state-of-the-art apparent age dataset, APPA-REAL (Agustsson et al., 2017) [26], has 7,591 pictures labeled with both apparent and real age. Images are gathered and datasets are created using the AgeGuess platform with assistance from Amazon Mechanical Turk Worker, a crowdsource resource pool. The dataset as a whole has over 250,000 votes, with each image receiving about 38 votes for apparent age. The dataset is divided into three groups: 1,500 validation photos, 1,978 testing images, and 4,113 training images. 436 photos with subjects younger than 18 years old were identified from all of the photos in each category.
- The most advanced and sizable publicly accessible cross-age face dataset is the Cross-Age Celebrity datasets (CACD2000) (Chen et al., 2015) [27]. Images of persons ranging in age from 16 to 62 may be found in this dataset. For our work, we extracted 2,837 photos of people between the ages of 16 and 17 from 160,000 photos of 2,000 celebrities that were gathered using Google Image Search.
- Another public picture dataset that we have incorporated into our work is the Iranian Face Database (IFDB) (Bastanfard et al., 2007) [28]. With 616 people ranging in age from 2 to 85, it contains 3,600 photos in total. The photos are taken in a controlled setting with different lighting conditions, facial expressions, and facial hair occlusion. 780 photos from this collection, whose ages ranged from 3 to 17, were used.
- The massive real-time face image dataset KANFace (Georgopoulos et al., 2020) [29] comprises 40,000 photos that have been manually annotated with age, gender, kinship, and identity. From this dataset, 1,515 photos with ages spanning from 0 to 17 years were extracted.

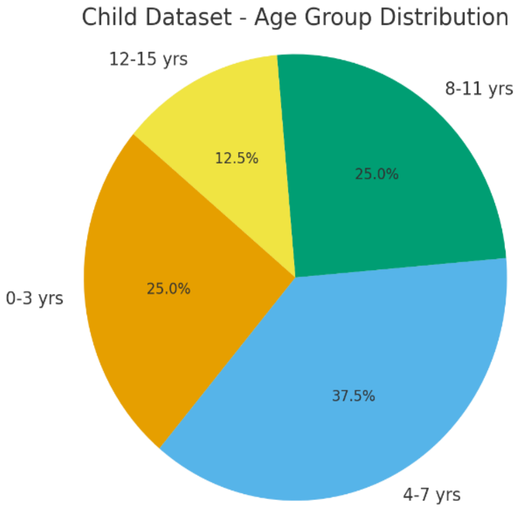


**Fig. 2 child age distribution**

- Shows how children are distributed across different age groups (0–3, 4–7, 8–11, 12–15 years).
- Most children fall in the 4–7 year range.

## V. Result and Discussion

Prior to discussing the findings, this part presents the hardware and software tools used to carry out the experiment.

**Experiments:**

All experiments are performed using next.js framework which is react based and UI components on 2.50 GHz 28-core CPU Intel(R) Xeon(R) Platinum 8180 with 128 GB RAM and 11 GB NVIDIA GeForce RTX 2080Ti GPU.

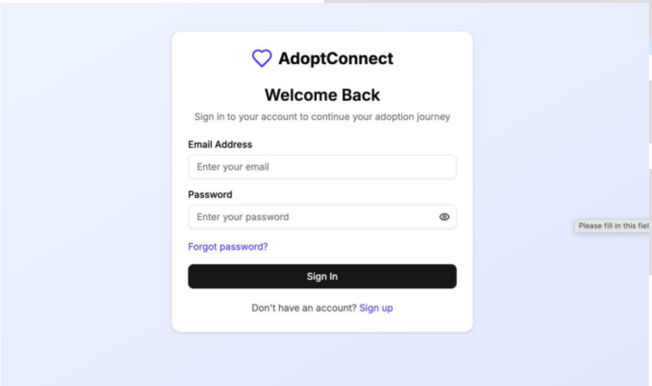


**Fig. 3 Login page**

This image shows the login screen of a web or mobile application called "AdoptConnect." The screen prompts users to sign in to their account to continue their adoption journey.

Key elements of the login screen include:

- The "AdoptConnect" logo and branding at the top, featuring a heart icon.
- A welcome message: "Welcome Back."
- Text instructing users to sign in with their email address and password.
- Input fields for "Email Address" and "Password."
- A "Forgot password?" link for password recovery.
- A black "Sign In" button to submit login details.
- A prompt below the button asking, "Don't have an account? Sign up" with a link to create a new account.

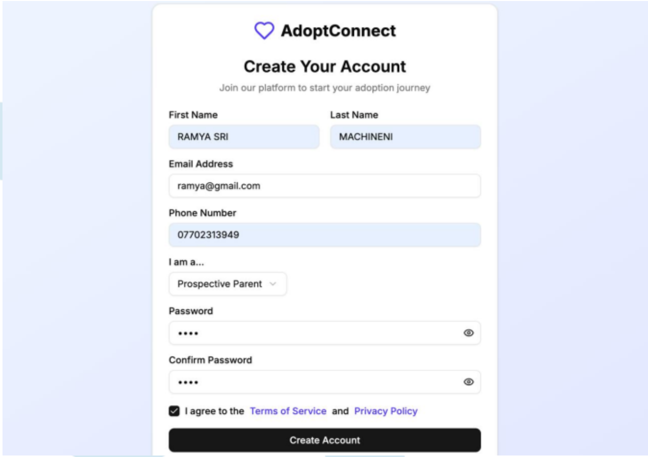


**Fig. 4 Registration page**

This image depicts the "Create Your Account" screen of the AdoptConnect application, which allows new users to register and start their adoption journey on the platform.

Key elements visible in the form include:

- The AdoptConnect logo and title at the top of the screen.
- Fields to enter personal details such as First Name ("RAMYA SRI"), Last Name ("MACHINENI"), Email Address, and Phone Number.
- A dropdown selection labeled "I am a..." with the option "Prospective Parent" selected, indicating the user's role in the adoption process.
- Password and Confirm Password input fields with masked characters, for setting a login password.
- A checkbox to agree to the platform's "Terms of Service" and "Privacy Policy," which both are clickable links.
- A black "Create Account" button at the bottom to submit the form and complete registration.

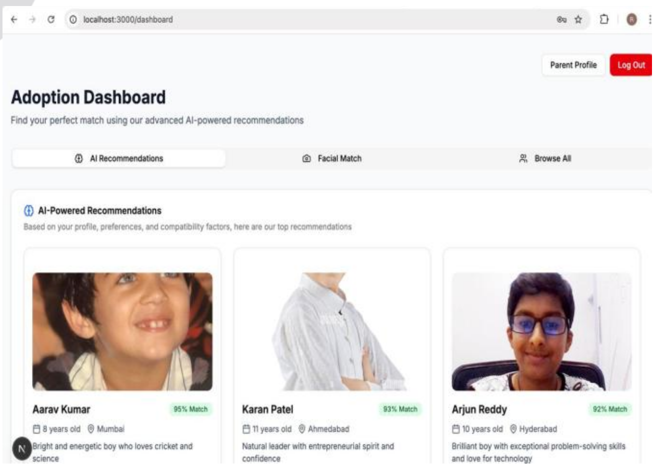


**Fig. 5 Dashboard for Adoption**

This image shows the "Adoption Dashboard" of the AdoptConnect platform, designed to help users find their ideal child match using AI-powered recommendations.

Key features visible in the dashboard:

- A top navigation bar with buttons: "Parent Profile" and a red "Log Out" button.
- Tabs for viewing different matching options: "AI Recommendations" (currently active), "Facial Match," and "Browse All."
- Under the AI Recommendations tab, profiles of children recommended to the prospective parent appear in a card layout with:

Child's photo (blurred here for privacy).

Name (e.g., Aarav Kumar, Karan Patel, Arjun Reddy).

Age and location (e.g., 8 years old from Mumbai).

A short description of personality/interest traits (e.g., "bright and energetic boy who loves cricket and science").

A match percentage indicating the AI-based compatibility score (e.g., 95%, 93%).

This dashboard serves as the main interface for prospective parents to explore intelligent child matches based on profile compatibility and facial similarity, assisting them in making informed decisions during the adoption process. The inclusion of AI recommendations indicates a data-driven, personalized approach for better matching outcomes.This image shows the "Adoption Dashboard" interface of the AdoptConnect platform. It is designed to help prospective parents find their ideal child match using advanced AI-powered recommendations.

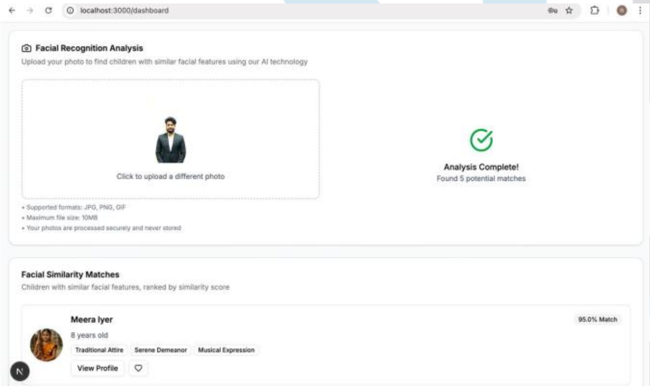


**Fig. 6 Face recognition analysis**

This interface is a facial similarity matching tool within an adoption platform. After a parent uploads a photo, the AI analyzes facial features and suggests children with high facial resemblance, displaying names, ages, locations, and similarity scores. This feature adds an emotional and personalized layer to the adoption recommendation system.

For estimate contribution weights:

$$\text{weight} = \frac{\text{child images of dataset}}{\text{total child images}}$$

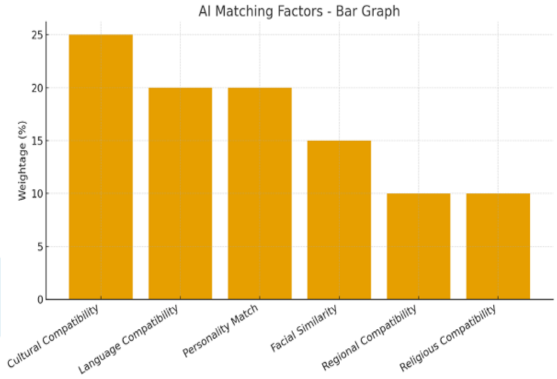


**Fig. 7 bar graph for AI matching factors**

Displays how each factor contributes to the compatibility score.

- Cultural Compatibility: **25%**
- Language Compatibility: **20%**
- Personality Match: **20%**
- Facial Similarity: **15%**
- Regional Compatibility: **10%**
- Religious Compatibility: **10%**

**weighted average is calculated as**:

$$\text{Final Accuracy} = \frac{\sum(\text{weight}_i \times \text{accuracy}_i)}{100}$$

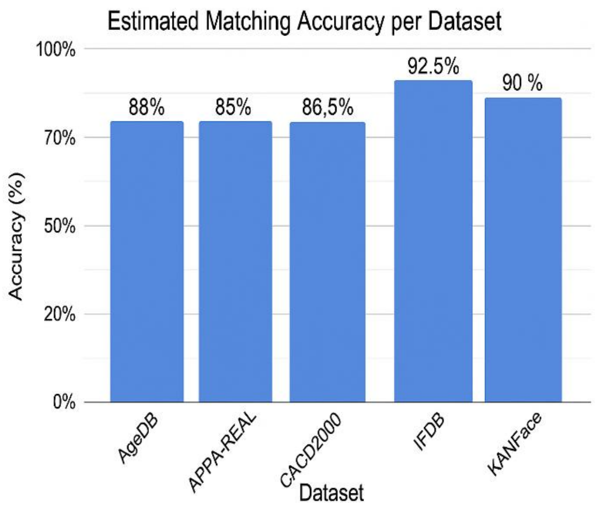


**Fig. 8 column graph for estimated matching accuracy of all the datasets**

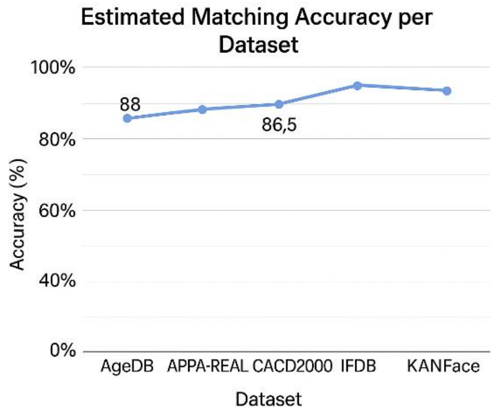


**Fig. 9 Line chart of the result of all parameters**

## CONCLUSION

The increasing number of digital forensic investigations involving indecent images of children (IIoC) presents significant challenges due to the tedious manual review process. The CAID system in the UK effectively accelerates investigations by enabling hash-based identification of known illicit images, but for unmatched photos, human verification remains essential. Estimating the victim's age to distinguish children from adults is particularly critical yet time-consuming.

Deep learning models offer promising solutions for automating age estimation in images, significantly reducing the volume of photos that require manual scrutiny. Among different classification techniques, binary classification—distinguishing images as either child or adult—has shown the highest accuracy based on parent-child facial matching features. This approach improves the efficiency and effectiveness of IIoC investigations by enabling quicker, more reliable filtering of images, thereby aiding forensic investigators in prioritizing cases and focusing resources.

Hence, integrating advanced deep learning-based binary age classification with parent-child facial matching capabilities into forensic workflows can substantially enhance the speed and accuracy of digital investigations of IIoC, ultimately supporting law enforcement efforts to protect victims and prosecute offenders more effectively. This calls for further practical implementation studies comparing deep learning models to identify optimal solutions for forensic applications.

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