Toward Detection of Child Exploitation Material: A Forensic Approach

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Abstract:- With continual advances in Internet capability, in addition to its global and decentralized nature, the Internet along with different social networking sites are experiencing a boom in demand and supply. Recent study found that the social networking sites like Facebook, Twitter, and MySpace are providing a forum for paedophiles to share child pornography. With the advent of sophisticated digital technology, Law Enforcement Agency (LEAs) around the world dealing with child pornography facing real challenge to combat with the technologically-savvy paedophiles. The major challenge in child pornography lies in authentic detection of children face in an image. The main objective of this research is to present a novel framework for a dedicated child face detection tool, where we will use child's face specific contextual contexts and visual cues that are based on new knowledge in terms of features or contexts representatives of child's skin and face. The proposed technique can estimate age categorically - adult or child based on a new hybrid feature descriptor, called *Luminance Invariant & Geometrical Relation based Descriptor* (LIGRD). LIGRD is composed of some low and high-level features, which are found to be effective in characterizing the local appearance in terms of chromaticity, texture, and geometric relational information of few facial visual cues simultaneously. Comparison of our experimental results with that of another recently published work reveals our proposed approach yields the highest precision and recall, and overall accuracy in recognition.

Keywords: Child, Adult, Porn, Face, Social networking, Skin, Exploitation, Craniofacial.

INTRODUCTION:

Before the advent of the Internet, clandestine porno magazine or porn-cinemas were the principal means for the production, distribution, exhibition, possessing and consumption of pornographic material. With its arrival, the Internet quickly became the prime medium for the distribution, transmission, and exhibition of such materials. Parallel to the changes in pornographic media, content has also changed, in that an increase in violence and misogyny could be found in magazines, on videotapes and on the Internet. Internet access to the computers and choice of social-networking sites are increasingly a modern day must have for children and young people around the world establishing new cultural norms and becoming mainstream within education. Clear majority of children and young people using the Internet for searching their educational stuff, playing games online, keeping themselves in touch with their social and online friends and as a source of perfectly innocent fun and games for the great majority of the time. In doing so, it is almost certain that at some stage these children and young people will be exposed to material that will cause trauma in their mind and possibly damage them psychologically. The worst part in that is, eventually it will lead them encounter organization or individuals who mean them injury. To follow potentially catastrophic consequences throughout a children's lifetime, he/she needs only one such encounter to go wrong. It is therefore no surprise that the Internet as well as the social networking sites pose a serious threat to our children who are vulnerable, either some or all the time while they are on the Internet. In fact, potential outcome of the Internet use is questionable as a little is understood yet of the potential problems and benefits associated with it, and the overall impact on the society from social benefit point of view that may arise. The risks posed by criminals who attempt to share, exchange, consume and produce child exploitation material, however, are clear, and law enforcement is faced with the difficult task of trying to deal with the sheer volume of material (and offences) in a streamlined and systematic way.

TABLE 1: **<u>WORLD INTERNET USAGE AND POPULATION STATISTICS' 2011 [1]</u>**

Regions	Population	Users	Penetration (%)
Africa	1.04 bil.	119 mil.	11.4%
Asia	3.88 bil.	922 mil.	23.8%
Europe	816 mil.	476 mil.	58.3%
Middle East	216 mil.	69 mil.	31.7%
N. America	347 mil.	272 mil.	78.3%
L. America	597 mil.	216 mil.	36.2%
Carib. Oceania/Aus	35 mil.	21 mil.	60.1%
Total	**6.93 bil.**	**2.10 bil.**	**30.2%**

One study in 2011 [1] revealed the Internet usage and population statistics across the globe as shown in Table 1. Another study in 2002 showed that across the whole world the number of children and young people regularly using Internet was running towards the eighty million mark at that time, and this number is increasing geometrically. A recent study showed that 27 million American children between the ages of 2 and 17 are active Internet users, and that is one in five of all US Internet users [2].

Children Internet pornographic statistics in TABLE II shows that onset of viewing pornography starts from early on. The average age of a child's first exposure to pornography is 11. A total of 90 percent of children ages 8-16 have viewed pornography online. Paedophiles try to exploit children using many character names that appeal to them such as "Pokemon" [1

TABLE II
CHILDREN INTERNET PORNOGRAPHY STATISTICS '2011

Average age of first Internet exposure to pornography	11 years old
Largest consumer of Internet pornography	35 - 49 age group
15-17 year olds having multiple hard-core exposures	80%
8-16 year olds having viewed porn online	90% (most while doing homework)
7-17 year olds who would freely give out home address	29%
7-17 year olds who would freely give out email address	14%
Children's character names	26

According to compiled figures from various news and research organizations, every second, $3; 075:64 is being spent on pornography. Every second, 28,258 internet users are viewing pornography. In that same seconds, 372 internet users are typing adult search terms into search engines. Every 39 minutes, a new pornographic video is being created in the U.S. In fact, legal pornography is huge but legal business. The pornography industry has larger revenues than Microsoft, Google, Amazon, eBay, Yahoo, Apple and Netflix combined. In 2006, worldwide pornography revenues ballooned to $97:06 billion. Pornographic revenue in Australia alone stands at US$ 2 billion (per capita AU$98:70) in 2006 [1].

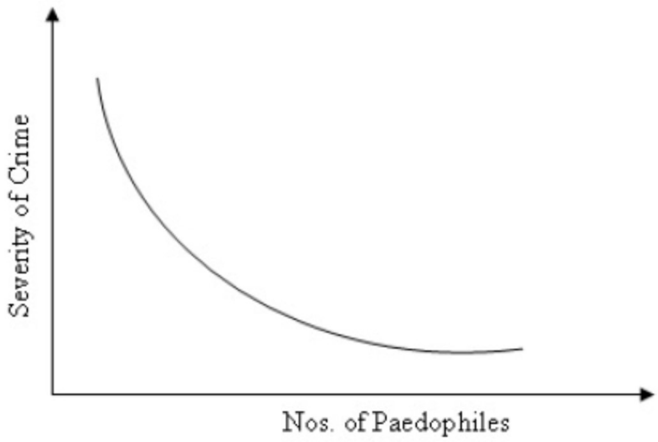

Fig. 1. Children Pornography Progression Model

Out of these statistics, a significant amount goes to purchasing child pornography, or has a link with adult pornography, if a **Progression Model** as shown in the Fig. 1 is assumed.

Some research suggests that becoming a paedophile is a gradual process that may start with viewing a variety of pornographic material, then gradually looking at the “teenage” sites and others, once the viewer has become desensitised to “legal” material. Over time, such users access more extreme material, in an endless quest for novelty, and these sites eventually point them to younger pictures, and finally, they may end up viewing illegal sites containing child pornography. Looking at ever-younger girls is a steady downward trend for the paedophiles [3], and the content can be extreme: the COPINE scale provides some indication of the extreme themes which are often pursued.

The annual turnover of child pornography businesses has been recently estimated at US billion globally [1]. More $3 billion globally. More than 100,000 web sites have been identified as engaging in the primary business of selling child porn to others [4],[5], & [6].

No doubt, the Internet has wormed its series of blissful tubes throughout our modern lives. It’s what people check in the morning, what people look at during the day, what entertains them at night. News, products, business opportunities, conversation, relationships, self-promotion, entertainments – what’s not on the Internet. An entire generation is growing up having never known a time without the Internet [37]. All of us will agree on is the ever-increasing dominant role this technology can play in our kid's daily lives, social networking sites in particular. With choices such as MySpace, Twitter, Xanga, Tumblr and the mother of all, Facebook – it's hard to find a teen now who never visited any of these sites. Currently, the most popular one, Facebook that started its journey in 2004 and opened to public in 2006 having 42 million active users, playing a dominant role in reshaping online behaviour and attitude of the modern-day Internet users. Its unparalleled ability to attract users using its virtual mode of communication and capability of providing almost everything an Internet user can be dreamt of, made it as an integral part of what people want and more importantly expect. Advances in the functionality and the usability of systems have provided criminals with opportunities to use - most often misuse technologies in ways in which they were never intended. Although these social networking sites specifically claims themselves as safe site, a series of investigations conducted by US multi-state investigations suggested that the Facebooks filters miserably fall short in blocking child pornography. The Facebook is failing to prevent child predators from posting suggestive and potentially illegal photographs of children on its website, a weekslong investigation by FoxNews.com reveals, despite its claim that its doing all it can to keep paedophile materials from being displayed. Facebook employs content-based filtering system that able to scan automatically few basic keywords most commonly being linked to child pornography as identified by the National Centre for Missing and Exploited Children (NCMEC). But FoxNews.com took two Facebook executives on a click-by-click tour of the Facebook in a lengthy telephonic interview on Oct. 6, 2010 bringing them face-to-face with some of its vile contents and forcing them to admit that their efforts to block child predators were not working at all. During a 90-minute phone interview with Facebook spokesman Simon Axten and the company's chief security officer, Joe Sullivan, FoxNews.com was able to expose the underbelly of Facebook. These executives were stunned viewing the extremity of graphic contents on the site. Even they are unaware of and unable to explain the extremely graphic content on their site [1].

In the said interview, FoxNews.com asked the executives to put the word PTHC in their sites search box and subsequently instructed to click on the first result identified as a public group Page called PTHC, with 197 members. When the executives tried to get access a post there it directed them to a video allegedly made on an 8-year-old boy being sexually abused. The term PTHC stands for Pre-Teen Hard Core - is linked with child sexual exploitation activity and materials that is frequently being used by the paedophiles, and it is on the NCMEC list of keywords. Later, when they are further asked to click on the profile of any of the group's members, the executives were steered into a subculture dedicated to using Facebook to traffic child pornography and to target and interact with children [10].

Recently, a US State Attorney General announced an investigation as the latest scrutiny for Facebook and similar sites, such as MySpace, that have been criticized for not regulating the interactions between adults and minors. In this investigation, undercover investigators were posing as children in online social networking website Facebook, where they were allegedly solicited by sexual predators and the users could easily access pornographic images. The undercover investigators also contacted Facebook and made complain as upset parents, but most often their complaints were ignored. In some cases, Facebook did respond by taking down inappropriate material [11].

It is therefore no surprise that child pornography is increasingly emerging as one of the most devastating artefacts of today's wired and global society. The potential field of research into criminal and deviant behaviour on the Internet is vast though few studies have yet been made to assess the magnitude of its impact on our society. Despite highly controversial and the subject of immense interest, researchers paid less attention to child pornography and its prevention on the internet.

Although weaving cyberspace into the fabric of our society, providing immense benefits to us, it is on the other hand, emerges as an increasingly visible problem to the mankind today. With the advent of sophisticated digital technology Law Enforcement Agency (LEA) around the world dealing with child pornography facing real challenge to combat with the technologically-savvy paedophiles. Recent growth in PCs at home and social-networking on the Internet combined with evolving field of digital technologies added a new dimension to paedophilia, resulting a convenient way to make their business by sharing horrific pictures of children being sexually abused - most often for profit. To combat child pornography, LEA are currently using some techniques that are both inefficient and relatively basic, resulting in a high failure rate of correct child porn image identification that could be used as forensic evidence in court. Rapid and accurate detection and prosecution
of child pornographers are currently handicapped due to a lack of appropriate technology - technologically-savvy child pornographers attempt to outwit law enforcing agencies by using newly developed and sophisticated state-of-the-art digital imaging and video processing facilities, equipment and software.

We propose a novel approach to implement a tool using a new model-based approach for detecting and identifying child face from images based on new knowledge in terms of child skin and face specific features or contexts. Successful implementation of the proposed approach combined with any existing state-of-the-art pornography detection techniques could be used as a dedicated tool to inspect huge volume of confiscate hard drives as anecdotal evidence. The recent growth in PCs at home and work (with Internet connectivity) provides paedophiles a convenient way to conduct their business, by sharing horrific pictures of children being sexually abused - often for profit. In addition to introducing strategies to try and reduce demand, often working against technologically savvy paedophiles, Law Enforcement Agencies (LEAs) around the world have had to deal with larger volumes of child pornography cases. To prosecute child pornography cases, LEAs typically use manual techniques that suffer from being slow, potentially inefficient and error-prone. Rapid and accurate detection (and prosecution) of paedophiles is somewhat handicapped due to a lack of appropriate technology – technologically savvy paedophiles attempt to outwit law enforcing agencies by using newly developed and sophisticated state-of-the-art digital imaging and video processing facilities, equipment and software. Literature suggests that LEA's digital forensic units currently are experiencing tremendous backlogs of cases due to the huge volume of child pornography related cases. A recent study showed that, in the Netherlands alone, the amount of data confiscated by the Police has increased from4.5 to 152 terabytes between 2003 and 2006 [7]. The huge amount of data must be manually inspected to find conclusive evidence for child pornography is a major challenge for law enforcing agencies. This inspection usually must be achieved in a very limited time frame, to keep a suspect and his PC in custody without a specific charge, or due to the statutory limits around the holding of evidence. The task of sifting through confiscated PC disk images to identify child pornography on the other hand is tedious, time consuming, emotionally taxing and difficult. As such, there is a pressing need for an accurate, faster and automated tool to detect and identify child pornographic images effectively regardless of its quality of production.

In addition, the proposed approach can be effectively integrated with any existing pornography detection approach to implement a dedicated real-time application tool to monitor and detect pedophilic activity on the Internet and other social networking via the Internet. For having a better and authenticated detection of pornographic evidence in an image, we can apply a dedicated and robust detection scheme based on pornography specific contextual constraints that are representatives of actual pornographic activity rather than relying on some heuristic skin region contents or ratios and features as employed in the existing techniques. A stochastic approach based on Markov Random Fields (MRF) modelling has been found to be effective in modelling contextually dependent physical phenomena especially in a degraded situation where source images suffer numerous imaging artefacts. Ongoing work on a solution to the problem of real-time pornography detection is undertaken by us, where we employ a novel stochastic vision model based on Markov Random Fields (MRF) prior. The MRF prior encodes the pornography specific contextual constraints to facilitate accurate and authenticated detection and identification of skin regions containing pornographic contents.

Fig. 2. Spanning 4 generations (Courtesy: The Mail, March 31, 2010)

In this work, we are interested in using the computational foundations of vision to help us design machine vision systems with applications to real-time detection and forensic investigation. Our broader research program aims to find solutions for some fundamental questions in computer vision. How can we recognize persons, guns, cars, boats and many other suspicious categories of objects in cluttered pictures? How can we gain knowledge of these classes in the first place? Can we provide the identical skill to computer?

We propose a novel approach to implement a tool for detecting and identifying children's faces from images. We utilize specific facial features or contexts, where low level skin features will detect the skin regions from images. We then exploit some visual cues from human faces to incorporate new knowledge in terms of spatial relationships among the low-level features along the contour of these visual cues.

However, identifying child (or adult) faces from images is a real challenge that has been in the literature with no general solution proposed so far. In many application areas - from identifying the age of actors by the classification review board, through to determining whether a porn image contains children or not - identifying age quickly accurately remains an unsolved problem. Detecting skin in images is a solved problem, but the literature suggests all the existing techniques are general - none of them are adult or child skin specific. A large number of existing state-of-the-run techniques for detecting adult skin are available, especially for nude person identification. In fact, pornography detection is a solved problem now. Therefore, this work is primarily aimed at child face detection to categorize a child face only, which is eventually applied to categorise the subject (whole image) either into child or adult.. Afterwards, a state-of-the-art pornography detector can be applied on the detected child images (the whole images – not the face only) to detect whether the image contains pornography contents or benign.

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Our hypothesis is that we can exploit children's face specific contextual cues in terms of skin and visual cues on face from images to perform the estimation, particularly where age is ex pressed categorically rather than continuously (child or adult, for example). For detecting children face from pornographic images, we will employ a novel children's facial model based on contextual cues representatives of children's skin and some crucial cues on human face, which is first of its kind. Detecting pornography in images is almost a solved problem now, the reason why the real challenge in child pornography detection lies in the detection of a child skin/face.

The article has five main sections. The Section II is largely descriptive on the existing pornography detection and skin detection techniques that have close resemblance with this work. Section III will describe our proposed research methodology followed by experimental results and discussion in Section IV. Finally, conclusion and further future research will be discussed in Section V.

RELATED WORK:

In general, pornography detection techniques are primarily based on two parts – skin modelling & classification technique and classification of pornographic contents. Skin classification technique comes first before applying pornographic content classifier as the latter is being applied on the skin patches as obtained from the former.

A. Existing Works on Child Pornography Protection

To the best of our knowledge, only a couple of literatures published from the University of Ontario Institute of Technology exist that are aimed at child pornography detection explicitly so far. Shupo et al. [8] suggested a network-based detection system that uses a stochastic weak estimator coupled with a linear classifier. The features that were extracted from the images - both training and testing, are some statistical properties from the labelled packets (those that have been stored into the pornographic and benign vectors). Later these vectors as obtained in training stage were fed into the classifier to train the classifier. The estimators they consider are the stochastic learning weak estimator (SLWE) and the maximum likelihood estimator (MLE). The SLWE is considered to be more accurate in dealing with non-stationary data1. To classify the image the authors employed four different distance functions - Euclidean distance, Weighted Euclidean distance, Variational distance, and Counter distance between two aforesaid feature vectors. The authors gathered a sanitized image dataset on child pornography from Toronto Police, Canada, while the non-child pornography image datasets were gathered using random images obtained from the Internet.

Being inspired by the outcome of the aforesaid work, A. A. Ibrahim extended [9] the research as a research Master project from the same institution, where he employed almost the same methodology but on an artificial image dataset this time. The author did not use any real-world child pornographic image; rather they employed an artificial dataset composed of adult pornographic images collected from the Internet.

B. Existing Works on Age Estimation

In age estimation, technology that has been proposed and implemented so far consists of content-based image analysis tools, like some low-level skin features and/or age specific features like wrinkle and other heuristic age features that are, in fact, not based on any adult or children specific facial contextual constraints.

Age estimation from digital facial images initiated by Kwon & Lobo [12], where they employed high resolution facial images to classify into three age groups - babies, young adults or senior adults. Authors reported 100% accuracy in classification but application on a limited database indicates that it is not applicable in real world applications. To accomplish the similar age group classification, they suggested another age classification technique based on craniofacial development theory and wrinkle analysis later [13]. Again, the approach is handicapped by limited dataset and thus very hard to assess its robustness while applied on real world large datasets. Hayashi et al. [14] employed wrinkle analysis along with geometric relationships between significant visual cues on human face to classify age into multiple groups at the five years intervals, which in fact, not a categorical age estimation technique rather it is focused on age-group wise classification.

Active Appearance Models have been employed by Lanitis et al. [15], where combined shape and texture parameters are extracted to estimate the age using three classifiers - simple quadratic fitting, shortest distance classifier, and Neural Network and age estimation accuracies of these classifiers are compared. Statistical modelling on ageing patterns (a sequence of personal facial age images) as suggested by Geng et al. [16] primarily based on the assumption that multiple images of different ages are available for each person. Yan et al. [17] suggested an algorithm, where the uncertainty of the age labels is considered in age estimation. Recently, Khoa et al. [18] suggested an approach combining Active Appearance Models (AAM) [19] with Support Vector Machine Regression to classify different ages. Initially, a classification is performed to classify age categorically (adult and children) using AAM's parameters then age-determination functions based on Support Vector Machine Regression are applied to estimate the age. In fact, classification using only AAM's parameter is not an ideal approach to classify age as appearance data exclusively are not able to provide adequate cues that are necessary to obtain accuracy in classification. This approach basically aimed at predicting specific age rather than categorical estimation like adult or children, the reason why authors recommended for further improvement especially in this part to make it a reliable categorical age estimation approach.

Geng et al. proposed an approach where ageing patterns are generated for each person in a dataset of facial images presenting every single subject at different ages [41]. The authors introduced a single sample, a collection of temporal face images for each subject, which is finally projected to a low dimensional space. At testing phase, an unseen face is substituted at multiple orientations in a pattern to indicate age of the subject using the process of minimizing the reconstruction error. Here, the authors suggest methods using unique characteristics of ageing like ageing patterns perform better than the standard classification techniques.

Ageing patterns using manifold learning is demonstrated by Fu and Huang [42], where they employed a manifold criterion based discriminative subspace learning to represent the low-dimensional ageing manifold. The authors suggest age estimation improves significantly when Regression is applied on the ageing manifold patterns. Based on this findings Guo et al. [43] applied a Support Vector Machine Regressor (SVR) to learn the relationship between age and coded face representations. Application of a local SVR trained with only ages within a small interval around the initial age estimate utilizing a refined age estimation using a local SVR is the key aspect of this particular work.

Error-Correcting Output Codes (ECOC) on the fused Gabor and LBP features of a face image are employed by Wang et al. [44] to categorise an individual into one of four possible age groups (child, teen, adult and senior adult). The authors found ECOC combined with AdaBoost or SVM solved the multiclass learning problem like age categorization. FG-NET and Morph datasets are employed to obtain experimental outcomes on its effectiveness and robustness in age categorization and found the algorithm based on the fused features performing better than the one based on Gabor alone or LBP alone.

Islam et al. [45] present a new framework for capturing facial image patterns that can be applied in categorical age estimation, which is primarily aimed at offering a novel approach to investigate and implement a child face detection technique that can estimate age categorically – adult or child based on a new hybrid feature descriptor. The novel hybrid feature descriptor LIGD (the luminance invariant geometric descriptor) is composed of some low and high-level features, which are found to be highly effective in characterizing the facial patterns in terms of local appearance. In local appearance estimation, chromaticity, texture, and positional information of few facial visual cues can be employed simultaneously.

Literature suggests, a dedicated approach for categorical age estimation especially adult and children is still missing, and the issue is not yet been addressed - the hole which this research is looking to fill.

OUR PROPOSED APPROACH:

Our proposed methodology will be based on a new image modelling on human face – both adult and child specific contextual constraints to be extracted from the pornographic images as to be obtained from an existing state-of-the-art pornography detection tool, where we will finally employ a Support Vector Machine (SVM) classifier to classify children and adult face image. The proposed approach is invariant to illumination changes, camera viewpoint, scaling, affine transformation and other imaging factors like shading, makeup and occlusion.

Child skin detection by machine offers considerable extent of challenges and difficulty to the machine vision community as complete knowledge on human visual system is unknown yet. Human ageing process especially on skin is not controlled by people's gene alone but also attributed to many factors like individual's lifestyle, health, race, occupation, cultural background and many more. Nothing significantly has been contributed in this particular area yet though much interest has been paid on adult skin detection over the last three decades that eventually kept the issue still open. Literature suggests that nothing has been attempted yet to address this issue. Automatic identification of children skin process needs at least some of the similar cues being used by human visual system in making judgment, resulting an effective and efficient way that attempts to quantify children's skin in ways that agree with human intuition. Defining such cues certainly will put this research to a considerable extent of challenge. It is still an open problem to extract general discriminative features for categorical age estimation using skin detection regardless of the negative influence of individual differences.

Smoothness of the skin's surface, hydration of the skin, collagen, elastin and glycosaminoglycan content have direct relation with the skin texture. Several key factors have gradual impact on these essential elements of skin. While a children's skin apparently looks like normal adult skin, there is significant differences in terms of both the structural and functional characteristics. A baby has wonderfully soft, smooth skin that differs significantly with adult skin. That lovely smooth skin of childhood undergoes some significant changes when we reach our teens and continues till adult. At this stage body produce an increased amount of hormones. A hormone called androgens starts to produce in both girls and boys to produce male hormones. Under the influence of this androgen the skin produces more oil (sebum), resulting a tendency for acne to develop. In addition, at the same time muscle starts to develop under the thick, soft, smooth and supple skin due to effective functioning of the stratum corneum and becomes visible at late teens, leaving a wavy skin surface all over the body. The anatomical differences between children and normal adult skin relate primarily to differences in the surfaces of the skin [38].

Human skin changes inexorably as people get older – no matter whatever the race, ethnicity, culture, age, and sex is. A young adult's skin is well hydrated, tends to be soft, smooth and supple, and has a natural translucency; while on the other hand, a more mature adult skin tends to function less well due to start of the ageing process, gradually leaving a dry and tend to feel tight skin with a rough texture and dull appearance. Wrinkles start to appear because of a gradual reduction in the water content of the stratum corneum, lipids and sebum, and some degree of photo damage due to sunburn [39]. Apart from the above, the major skin tone problem that occurs with time is the darkening of skin colour due to the skin cell damage from prolonged sunlight exposure. The top most cell layer in our skin absorbs the natural colouring pigment, melanin, allowing gradual darkening of skin colour due to over absorption. Melanin is produced in the basal cell layer of human skin and dead cells on the surface absorb this colouring pigment. Use of cosmetics, soap, shower gel, and body lotion add an extra degree in gradual skin tone deterioration process. A gradual decline in adult skin tone due to numerous factors makes substantial differences with that of children's skin, favouring us to detect children's skin even with our naked eyes. The answer of the question, how people perceive the difference between two objects is still missing as complete knowledge on human visual system is unknown yet. So, our prime focus is to apply at least few of the cues that human visual system applies in distinguishing different objects in our approach to detect children's skin offering an effective and efficient way that attempts to quantify shape and appearance in ways that agree with human intuition.

A. Image Pre-processing Stage

Noise embedded in a data set results in some corrupted values for the data set. This was particularly true in face/ skin segmentation/ classification problem where data sets are usually noisy due to diverse imaging artifacts like low intensity, intensity inhomogeneity, and shadow. In addition, noise attributed to the camera electronics and lens characteristics made the problem harder. More noise means more uncertainty. So, we apply a low-pass filter to our dataset to minimize these noises originated by the aforesaid inherent imaging artefacts. To remove other difficulties like intensity inhomogeneity, unclear edges of different segments or objects shadows, shading and highlight effects in image dataset, we apply adaptive histogram equalization. Adaptive histogram equalization enhances the contrast of the grayscale image by transforming the values using contrast-limited adaptive histogram equalization. Contrast-limited adaptive histogram equalization operates on small regions in the image, called tiles, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the desired histogram shape for the image tiles. The neighbouring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image [36].

B. Low Level Feature Generation

Research reveals that accuracy in skin segmentation/ classification primarily relies on colour and texture features. Research also found that segmentation based purely on colour is more sensitive to local variation, but provides sharp boundaries [20], [21], & [22]. On the other hand, segmentation based purely on texture feature results in fuzzy boundaries, but usually homogenous regions. In other words, colour and texture-based segmentation are in combination capable of producing sharp boundaries and homogenous regions. In fact, an individual object can be detected more efficiently with the combined features of colour and texture than either the colour or texture feature used independently. As a result, segmentation with combined colour and texture outperforms others in terms of sharpness and homogeneity [20], [21], [22] & [23].

One of the primary goals of this proposed model is to find a suitable low-level feature set composed of color and texture features that are able to discriminate skin and non-skin region effectively with maximum accuracy. Although RGB is the most commonly used color space unfortunately, it is not perceptually uniform and not corresponds to the human visual system. Literature suggests *YCrCb*, *CIE-Luv*, *CIE-Lab*, and normalized rgb are most popular choice in skin detection. Similarly, on the other hand, Wavelet Transform, Gabor filters, and MSRAR have been found to be effective in encoding texture details - coarser and finer both while other texture descriptors are not ideal in complex situations like security & surveillance, bio-medical, bio-engineering, material sciences, mining, mineral and metallurgy, where situation demands a more sensitive texture discriminative ability [20], [21], [22] & [23]. We employ 12 possible combinations of low level feature sets out of these 4 color spaces and 3 texture descriptors on 100 face images from the NCMEC [24] and FG-NET [25] database and then fed these multidimensional feature sets sequentially as an input into a Nave Bayes' classifier to perform segmentation using an adaptive thresholding technique. Since people with different skins have different likelihood, an adaptive thresholding technique is required to achieve the optimal threshold value for each image. Here, we discard the brightness / luminosity components from the color spaces to make the feature sets invariant to illumination.

Classification error is defined as;

$$Classification\ Error: FP(\%) + FN(\%)$$

Our study (Table III) clearly demonstrates the superiority of Chroma *YCrCb+Wavelet* compared with its other competitor as it outperforms them in all the three metrics (False Positive, False Negative, and Classification Error).

C. Color Feature

20 skin patches are collected by just cropped off from the face images. A new low level color feature is derived utilizing the pure chromatic information (*Cr* and *Cb*) of the original color model as;

$$Chroma\ C(r,b) = C(r,b) - C(r,b)mean \tag{1}$$

TABLE III: PERFORMANCE COMPARISON OF DIFFERENT COLOR AND TEXTURE SEGMENTATION/FEATURE COMBINATION IN SKIN CLASSIFICATION.

Low level Featr. Comb.	Different Metrics		
	FP(%)	FN(%)	Classn. Err.(%)
Chroma_YCrCb +Gabor	6.98	5.83	12.81
Chroma_YCrCb +Wavelet	6.71	4.36	11.07
Chroma_YCrCb +MRSAR	8.9	8.57	17.56
Chroma_CIE-Luv +Gabor	7.14	5.89	13.03
Chroma_CIE-Luv +Wavelet	7.69	6.41	14.10
Chroma_CIE-Luv +MRSAR	9.12	7.97	17.09
Chroma_CIE-Lab +Gabor	8.98	6.58	15.56
Chroma_CIE-Lab +Wavelet	7.77	8.39	16.16
Chroma_CIE-Lab +MRSAR	11.06	10.45	21.51
Chroma_rgb +Gabor	9.56	6.12	15.68
Chroma_rgb +Wavelet	10.78	8.23	19.01
Chroma_rgb +MRSAR	10.36	9.87	20.23

Where $C_{(r,b)}mean = \frac{\sum_{n=1}^{N} C_{(r,b)}}{N}$ and N = Nos. of pixels in a single skin patch.

1) Texture Feature: Texture characterizes local variations of image color or intensity. There is no formal or unique definition of texture, even though texture-based methods are commonly used in computer vision. Each texture analysis method defines texture from its own context. However, the neighbourhood property is a common similarity among all the available texture definitions/ descriptions. So, we can defin texture as an image feature which is characterized by the gray value or color pattern in a neighbourhood surrounding the pixel.

Smoothness of the skin's surface, hydration of the skin, collagen, elastin and glycosaminoglycan content have direct relation with the skin texture. Several key factors like hormones, diet, sunlight, and various environmental factors have gradual impact on these essential elements of skin. While a children's skin apparently looks similar to normal adult skin, there is significant differences in terms of both the structural and functional characteristics. Some primary impacts occur in the soft-tissue, in the formation of wrinkles, lines, ptosis, and soft tissue while children enter their adulthood. Here, we need to have a powerful texture descriptor that has the ability to encode this subtle texture information effectively.

Transform Domain Feature that refers to a mathematical representation of an image characteristic. There are several texture classifications using transform domain features in the past, such as discrete Fourier transform (DFT), and discrete wavelet transform (DWT). In this particular work, we employ DWT considering its effectiveness in capturing subtle texture information compared with other texture descriptors. Wavelet analysis breaks up a signal into shifted and scaled versions of have collected the original wavelet (mother wavelet) which refers to decomposition of a signal with a family of basis functions obtained through translation and dilation of a special [26]. Moments of wavelet coefficients in various frequency bands have been shown to be effective for representing [27].

Decomposition of textures is one of the keys to access characteristics of textures in different scales and a wavelet transform can do such decomposition. The wavelet transform is based on using an orthonormal family of basis functions. A wavelet expansion is a Fourier series expansion but is define by a two-parameter family of functions;

$$f(x) = \sum_{m,n} C_{m,n} \psi_{m,n}(x) \qquad (2)$$

Where and are integers, the functions $\psi_{m,n}(x)$ are the wavelet expansion functions and the two-parameter expansion coefficient, are called the discrete wavelet transform (DWT) coefficients of $f(x)$

The coefficients are given by

$$C_{m,n} = \int_{-\infty}^{+\infty} f(x) \psi_{m,n}(x) \qquad (3)$$

define another low-level texture feature employing the diagonal, horizontal, and vertical coefficients as yielded by the DWT as;

$$dwt_{(d,h,v)} = Coef_{(d,h,v)} - Coef_{(d,h,v)}mean \qquad (4)$$

where $Coef_{(d,h,v)}mean = \frac{\sum_{n=1}^{N} Coef_{(d.h.v)}}{N}$. Here,
N = Nos. of pixels in a single skin patch and $Coef_{(d,h,v)}$ denotes diagonal, horizontal, and vertical coefficients.

2) Local Binary Feature: Local binary patterns (LBP) has been found to be a powerful feature allowing a classifier or detector to exploit fundamental properties of local image texture efficiently and effectively in a classification or matching. Applying LBP on an image yields occurrence histogram, which is a powerful texture descriptor that contains information about the distribution of the local micro-patterns like edges, spots, flat areas, over the image region. Label for every pixel of the image is assigned by the original LBP operator applying a thresholding technique on the centre pixel with his 3x3 neighbourhood. Local Binary Patterns were originally introduced as a texture descriptor by Ojala [28], and have subsequently been employed as face and expression identification features [29] & [30].

By assigning a binomial factor 2^{p} for each sign $S(g_p - g_c)$ in the following equation, a unique number that characterizes the spatial structure of the local image texture;

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \quad s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \qquad (5)$$

Where, P = nos. of neighbouring pixels, R = radius of the neighbourhood, g_p = gray values of circularly symmetric neighbourhood, and g_c = gray value of centre pixel [40].

LBP encode a thresholded local neighbourhood at the gray value of the centre pixel in the form of a binary pattern and remain constant as long as the order of gray values in the image are not changed. In fact, this is highly discriminative and robust local texture operator that encodes the occurrences of the various patterns in the neighbourhood of each pixel in a *P*-dimensional histogram. In this work, we employed LBP on two chromatic channels $Chroma_r$ and $Chroma_b$ to encode chromatic channel-wise texture description to have
better texture discriminative ability.

3) Facial Appearance Feature: In order to incorporate new knowledge on face in terms of location and inter-relationships among the visual cues like eyes, eyebrows, mouth, nose, chin, side of face, we use cranio-facial development theory [13], which states that the appropriate mathematical model to describe the growth of a person's head from infancy to adulthood is the revised cardioid strain transformation, cardioid strain transformation, written in a polar form as $\theta' = \theta, R' = R(1 = k(1 - \cos\theta))$where θ is the angle from the *Y*-axis, *R* is the radius of circle, *k* is a parameter that increases over time, and (R', θ') ,s are the successive growths of the circle over time. According to the revised cardioid strain transformation, top of the head can be visualized as a series of ever growing circles all attached to a common tangent "base" point resulting growth of the lower parts of the face is more remarkable than that of the upper parts. Thus, for example, within the top and bottom margins of the head, eyes occupy an higher position in an adult than in a child, which is not due to eye migration, but instead to an outgrowing and dropping of the chin and jaw.

Localization of these facial cues is performed using iterative framework as described in [31]. One these facial cues are localized, in the next step, geometric ratios are computed using their localized position that distinguish children from adult. A six of ratios are computed by the authors utilizing the relationships between these primary visual features or cues out of which our proposed approach employs the first 5 ratios only as shown in Fig. 3 and computed in [31]. These evaluated ratios only need the automatic localization of the primary features such as eyes, nose, mouth, chin, and virtual top of head. Ratio 1 is the *T* -ratio formed by two segments – the segment *T1* joining the two eyes and the segment *T2* between the midpoint of *T1* and the nose. Ratio 2 is the *T* -ratio formed by two segments - the segment *T1* as above, and the segment *T3* between the midpoint of *T1* and the mouth. Ratio 3 is the *T* -ratio formed by two segments - the segment *T1* as above, and the segment *T4* between the midpoint of *T1* and the chin. Ratio 4 is the ratio of the segment representing the difference in height between nose and eye-midpoint, and the segment representing the difference in height between mouth and eye midpoint. Ratio 5 is the ratio of the segment representing the difference in height between mouth and eye-midpoint, and the segment representing the difference in height between chin and eye-midpoint. Ratio 6 is the height of the eyes within the top and bottom head-margins [31].

In addition to these ratios, we introduce a novel ratio that involves eyebrows and nose. Localization of nose is done according to the technique as depicted in [31]. Here, we need to model eyebrows as a deformable template, which is described by a number of parameters. This deformable template is specified by a set of parameters which enables a priori knowledge about the expected shape of the features to guide the detection process. The size and other parameters of this template are flexible enough to match itself to actual eyebrows in an image. The parameters as obtained from the final iteration are used to describe the eyebrows. This deformable template interacts with the image dynamically. An energy function is defined which contains terms attracting the template to salient features such as edges and valleys in the image intensity and the intensity itself. Gradient Descent, a state-of-the-art energy minimization technique is employed to get the best fit with the image. Initial parameters are determined by pre-processing. In each iteration, these parameters are updated that corresponds to altering the position, orientation, size, and other relevant properties of the template.

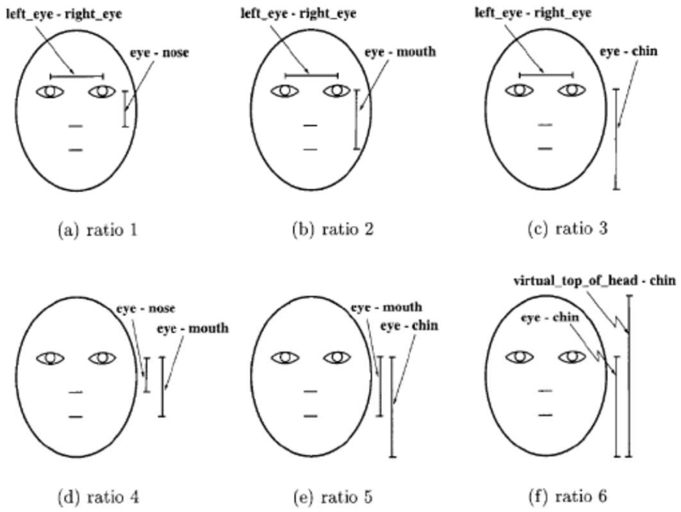

Fig. 3. **Six cranio-spatial ratios.** ***Courtesy: Age classification from facial images [31]***

We propose the Ratio 7 which is the *T* -ratio formed by two segments - the segment *T5* joining the midpoints of two eyebrows and the segment *T6* between the outer ends of the eyebrows and the nose as shown in Fig. 4.

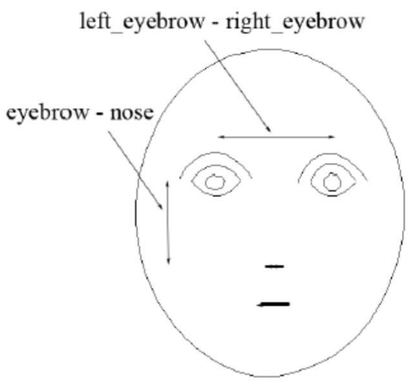

Fig. 4. **Our newly proposed ratio**

The Eyebrow Template: The deformable templates act on three representations of the image, as well as on the image itself. These representations are chosen to extract properties of the image, such as peaks and valleys in the image intensity and places where the image intensity changes quickly. An additional representation could be added to describe textural properties. An advantage of using these representations is that the templates need only be specified in simple terms. Ability to long range interactions to occur is another advantage of using these representations. These representations do not have to be very precise, and they can be calculated simply. For details, please see [35].

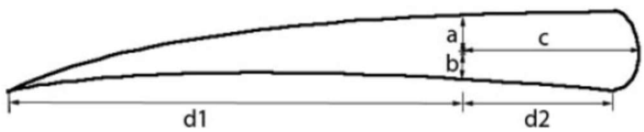

Fig. 5. **Eyebrow deformable template. Eyebrow is arbitrarily centered on a point $\overline{x}$. Area of the eyebrow is bounded by the upper and lower parabola located at a distance $d1$ and $d2$ from the centre $\overline{x}$, and the right hand side parabola located at a distance a and b from the same centre.**

Our present methods involve using morphological filter [32], [33] & [34] to extract these features. The advantage of these methods for extracting the edge, valley, and peak fields is they yield measures of the strengths of feature in question.

We define an eyebrow template as shown in Fig. 5 in terms of a coordinate system (x,y) positioned at a point $\overline{x}$ (assumed as centre of mass on an eyebrow shaped flat rigid body). The template we defined as follows: (1) The edges at the bottom of eyebrow is represented by a parabola P_b

$$y_e(x) = (a)\left\{1 - \frac{4}{(d1+d2)^2}\left[\overline{x} - \left(\frac{d2-d1}{2}\right)\right]^2\right\} \qquad (6)$$

(2) The edge at the top of eyebrow is represented by a parabola P_t

$$y_v(x) = (b)\left\{1 - \frac{4}{(d1+d2)^2}\left[\overline{x} - \left(\frac{d2-d1}{2}\right)\right]^2\right\} \quad (7)$$

(3) The edges at the inner end (close to nose) of eyebrow is represented by another parabola P_i

$$y_i(x) = (c)\left\{1 - \frac{4}{(a+b)^2}\left[\overline{x} - \left(\frac{b-a}{2}\right)\right]^2\right\} \quad (8)$$

The template depends on 6 parameters $\overline{g} = (\overline{x}, a, b, c, d1, \& \quad d2)$ and its potential Energy function E_M is given by

$$E_M = E_e + E_v + E_l + E_m \quad (9)$$

where the edge potential, E_e is computed along the upper, lower and side parabola, is

$$E_e = -\frac{\beta_1}{|P_b|}\int_{P_b}\Phi_e(\overline{x})ds - \frac{\beta_2}{|P_t|}\int_{P_t}\Phi_e(\overline{x})ds - \frac{\beta_3}{|P_i|}\int_{P_i}\Phi_e(\overline{x})ds \quad (10)$$

where Φ_e is edge potential computed earlier using morphological operator.

The valley potential, E_v is specified by the integral over the interior of the eyebrow divided by the area of the eyebrow

$$E_v = -\frac{e_1}{|R_e|}\int_{R_e}\Phi_v(\overline{x})dA \quad (11)$$

Φ_v is valley potential computed in a similar manner like edge potential above.

The internal potentials are

$$E_l = \frac{k_1}{2}(d1 - d2)$$
$$E_m = \frac{k_2}{2}\left[\frac{c-(a+b)}{(a-b)-(d1-d2)}\right]^2 \quad (12)$$

The internal parameter, E_l attempts to place the centre of the eyebrow in an arbitrarily middle position while another internal parameter E_m helps prevent the upper boundary getting pulled up to the lower boundary and the nose.

Typical values of the constants are $\beta_1 \approx 400, \beta_2 \approx$

$$150, \beta_3 \approx 300, k_1 \approx 0.2, k_2 \approx 0.1, \text{ and } e_1 \approx 1000.$$

Updating of these parameters are done by gradient descent.

Tracking: Deformable template can be applied for tracking in a straight forward manner where tracking eyebrows are done automatically given an initial position and a set of potential fields. We initialize the template manually for the first time but in subsequent frames we use initial position as the best fit of the preceding frame. This process succeeds only as long as the best fit at time $(t-1)$ lies in the basin of attraction of the system at time *t*. A dynamic sequence of eyebrow template on both eyebrows is graphically illustrated in Fig. 6.

Fig. 6. **A dynamic sequence of eyebrow template on both eyebrows. Final state of the template acting on the eyebrows is shown on the right column of the bottom row.**

D. Classification

For model training, an image set *X* (matrix), where *n* is the image number and *m* is the feature dimension, the face estimation expression can be represented as,
X = $[x_1, x_2, x_3, ..., x_n], x_i \in \mathcal{R}_m$. The categorical age label for the image x_i is denoted as $l_i \in \{1, -1\}$. The task is to predict the categorical age label of an input image *X* using binary Classification.

In this work, we use the Support Vector Machine for binary classification.

In this scenario, a hyperplane can be described by

$$w.x + b = 0 \tag{13}$$

where, *w* is normal to the hyperplane, and $\frac{b}{||w||}$ is the perpendicular distance from the hyperplane to the origin.

Now, we create plane *H*, where

$$H_{ij} = y_i y_j x_i . x_j \tag{14}$$

Find a Lagrange multiplier ∝ using a QP solver so that

$$\Sigma_{i=1}^{K} \alpha_i - \frac{1}{2}\alpha^T H \alpha \tag{15}$$

Is maximized, satisfying the constraints $\alpha_{1 \geq 0} \; \forall_i$ and $\sum_{i=0}^{K} \alpha_i y_i = 0$

Now, we calculate

$$w = \Sigma_{i=1}^{K} \alpha_i y_i x_i \tag{16}$$

where x_i and y_i are class label and training vectors respectively. Once feature extraction is done, each face image is represented as an assembly of cropped skin patches, and geometrical constraints expressed as ratios. We use low level features as described above of these skin patches along with geometrical ratios on primary visual cues as features for categorical age estimation. Here, we employ first five ratios as computed by Kwon & Lobo [31] along with our newly proposed ratio 7 as formulated earlier. Doing so, we get a high dimensional feature vector representative of each individual face, which we call *Luminance Invariant & Geometrical Relation based Descriptor (LIGRD)*;

$$LIGRD = x_i = \left[\sum_{n=1}^{N} (Chroma_{(r,b)} + dwt_{(d,h,v)} + lbp_{(r,b)}) + Ratio_{(1,2,3,4,5,7)} \right] \tag{17}$$

where, *N* = nos. of skin samples.

Determine the set of Support Vectors S by finding the indices such that $\alpha_i > 0$. Now, *b* is computed as;

$$b = \frac{1}{N_s}(y_s - \sum_{m\epsilon S} \alpha_m y_m x_m . x_s) \tag{18}$$

Each new each feature vector x_i is classified by evaluating

$$y^{'} = sgn(w.x^{'} + b) \tag{19}$$

EXPERIMENTAL RESULTS:

In this particular research, we have outlined a computational framework for categorical age estimation (adult and children) from facial images irrespective of gender. First, the low-level features are extracted from the skin patches of facial images. Next, ratios are computed from the primary cues (eyes, eyebrows, nose, mouth, & chin) as localized by the respective deformable templates. Combining these low levels and high level features forms a powerful descriptor that is able to distinguish between adult and children with maximum accuracy.

Comparison of our experimental results with that of another recently published work reveals our proposed approach yields the highest precision and recall, and overall accuracy in recognition. For quantitative performance comparison, so far, we have not found any existing technique that estimate age in explicitly two categories - adult and children. So, we do not any choice other than comparing our results with a recent relevant work [18], though it is not aimed to categorical age estimation as reported by the authors. Further, the authors have recommended further improvement in their categorical age estimation (baby, adult, & senior) part to make it a reliable categorical age estimation approach.

For quantitative performance comparison, a popular measure, called Precision and Recall (Eq. 20 & 21), based on True Positive (TP), True Negative, False Positive (FP), and False Negative (FN) is applied on both - our experimental results and the results obtained from Islam et al. [ ] to evaluate the classification performance of our novel approach. Apart from the Precision and Recall, we also compared accuracy (Eq. 22) of our approach with the same.

$$Precision = \frac{TP}{TP + FP} \tag{20}$$

$$Recall = \frac{TP}{TP + FN} \tag{21}$$

$$Accuracy = \frac{TP + TN}{P + N} \tag{22}$$

Where, *P* = Nos. of positive sample and *N* = Nos. of negative sample.

A. Training

We have sourced 400 children face images from different database as shown in TABLE-IV below [24], [25], [46]. After, different pre-processing steps (denoising, gamma correction, enhancement, and normalization, feature extraction done on these facial images. No negative sample (adult face) has been taken into consideration.

TABLE IV: FACIAL IMAGES TAKEN FROM DIFFERENT DATABASES FOR TRAINING.

Method	*Children*
FG-NET	100
NCMEC	100
LAG	200

B. Testing

The recognition results were evaluated on a dataset composed of 400 images (not included in the training set) from the same datasets shared equally as shown in Table V. Out of these 400 images 100 adult face images were taken equally from each of the FG-NET & LAG database.

TABLE V: FACIAL IMAGES TAKEN FROM DIFFERENT DATABASES FOR TESTING.

Method	*Adult*	*Children*	*Total*
FG-NET	50	100	150
NCMEC	0	100	100
LAG	50	100	150

TABLE VI: COMPARISON OF PERFORMANCE OF OUR PROPOSED METHOD WITH ANOTHER EXISTING METHOD.

Methods	*TP*	*FP*	*TN*	*FN*
ICSIPA	270	14	103	13
Proposed	276	9	104	11

TABLE VII: COMPARISON OF ACCURACY OF OUR PROPOSED METHOD WITH OTHER EXISTING METHOD.

Methods	*Precision (%)*	*Recall (%)*	*Accuracy (%)*
ICSIPA	95	95	93
Proposed	91	96	95

We compared the performance comparison and accuracy of our proposed approach with another existing methods and found the proposed approach outperformed the existing approach significantly as shown in the Table VI & VII.

CONCLUSION

We have proposed a novel child face model, where low level features detect child and adult face with maximum accuracy. It can be applied as a dedicated tool for detecting and/or monitoring child pornography while integrated with any existing pornography detection approach. As feature extraction is the key in classification, in this work, we proposed few novel low and high-level feature extraction techniques to achieve maximum accuracy in classification while applied with few existing techniques. To the best of our knowledge, this is the first of its kind which is able to recognize a child and adult face image effectively with highest accuracy and thus paves the way for research in this area to not only help categorical age detection, but also to identify real contents using contextual constraints in the detected skin regions, which may contribute significantly in security & surveillance, human body parts identification, anatomical & dermatological applications and even in marketing - tailoring advertising in shop windows based on the age of shoppers walking past. These alternate uses for the outcomes of this particular work provide extended usefulness and avenues.

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