LONGITUDINAL ANALYSIS OF MASK AND NO-MASK ON CHILD FACE RECOGNITION

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ABSTRACT

Face is one of the most widely employed traits for person recognition, even for large-scale applications. Despite technological advancements in face recognition systems (FRS), they still face obstacles caused by pose, expression, occlusion, and aging variations. Owing to the COVID-19 pandemic, contactless identity verification has become exceedingly vital. Recently, few studies have been conducted on the effect of face mask on adult FRS. However, the impact of aging with face mask on child subject recognition has not been adequately explored. Thus, the objective of this study is analyzing the child longitudinal impact together with face mask and other covariates on FRS. Specifically, we performed a comparative investigation of three top performing publicly and a post-COVID-19 commercial-off-the-shelf (COTS) system under child cross-age verification and identification settings using our generated synthetic mask and no-mask samples. Furthermore, we investigated the longitudinal consequence of eyeglasses with mask and no-mask. The study exploited no-mask longitudinal child face dataset (i.e., extended Indian Child Longitudinal Face Dataset) that contains 26,258 face images of 7,473 subjects in the age group of [2, 18] over an average time span of 3.35 years. Due to the combined effects of face mask and aging, the FaceNet, PFE, ArcFace, and COTS verification accuracies decrease approximately 25%, 22%, 18%, 12%, respectively.

Index Terms—Cross-Age Face Recognition, Mask Face Recognition, Longitudinal Mask Dataset, Child Face Recognition

1. INTRODUCTION

Nowadays, face recognition systems under face mask is getting much more momentum. For instance, the work in [1, 2] evaluated verification performance on both real and synthetic masks. It was later extended in [3] to analyze the human experts and automatic recognition systems on unmasked, real masked, and synthetic mask on adult dataset.

![Fig. 1: Left: no-mask subject. Right: mask subject. Center image represents a enrollment image and branches are images of same subject at different ages. Here, T1, T2, T3, T4, T5, and T6 denote time lapses between enrollment and subsequent acquired images. Age at the time of image acquisition (in years) is given below each images.](image)

Besides face mask, face aging is also a vital co-variate that negatively affect automated face recognition systems, especially for child subjects. For example, Deb et al. [4] fused COTS and FaceNet [5] scores, and attained 80.56% and 53.33% verification accuracy, respectively, for a time lapse of 1 and 3 years between enrollment and probe images for subjects of age [2–18] years old. The work in [6] investigated five top performing COTS matchers, two government matchers and one open-source face recognition system on Wild Child Celebrity and LFW [7] datasets, and obtained maximum of 78.20% and 85.2%, respectively, verification and Rank-1 identification accuracy. The study also showed each algorithm’s negative bias towards children compared to adult face samples. There exist several mask face datasets [8, 9, 10] but they mainly contain adult faces and caucasian and north Asian demography. To the best of our knowledge, no study has explored the combined effect of aging and mask on face recognition when the subjects are children. Also, no prior works explicitly evaluated the longitudinal identification performance when probe samples are with mask and gallery samples are without mask and vice versa. Therefore, this work analyzes the practical covariates (e.g., elapsed time, age, sex, with mask and no-mask, and eyeglasses with mask and no-mask). Namely, we present a longitudinal study using

| Table 1: Number of genuine pairs according to time lapses. |
|---------------------------------|
| **Protocol** | **Gender** | **Δ T1** | **Δ T2** | **Δ T3** | **Δ T4** | **Δ T5** | **Δ T6** |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| No-mask | Girls | 2,568 | 2,622 | 2,772 | 1,870 | 8,11 | 3,48 |
|   | Boys | 2,596 | 2,618 | 2,355 | 1,452 | 8,05 | 3,33 |
| Mask | Girls | 2,519 | 2,533 | 1,663 | 1,034 | 5,46 | 2,54 |
|   | Boys | 2,506 | 2,618 | 2,355 | 1,452 | 8,05 | 3,33 |
one of the largest, deepest, and longest (in terms of number of subjects, number of images per subject, and time spans of subject images) child face dataset. Thus, this study investigated the above-mentioned directions by extending Children Longitudinal Face (CLF) [4,11] dataset. We simulated the synthetic mask over all face images by using open source tool Masked Face-Net [8] on the children dataset while keeping faces’ longitudinal nature, as also shown in Fig 1. There are several venues where child face recognition systems are needed, e.g., finding missing children [4,12], de-duplication of identification documents (e.g., minors passport validation and diver license) [13,14] and school attendance during COVID-19 pandemic with mandatory mask [15, 16]. The resulting MaskedFace-ECLF contains 24,653 masked face images (12,507 boys and 12,146 girls) of 7,457 subjects (3,732 boys, 3,725 girls).

3. EXPERIMENTS SETUP
To analyze real-world scenarios of child longitudinal study with and without mask, following four face recognition protocols were investigated, as shown in Fig 3.

BCADGMDV vs. CADGMDV: This protocol evaluates cross-age face verification performance under no-mask and mask with disjoint gender influence. It is done by performing 1:1 comparison, where enrollment image (first acquired image at youngest age) is compared to subsequent face images of the same subject at greater age than enrollment. We named this protocol Baseline Cross-Age Disjoint Gender No-Masked Face Verification vs. Cross-Age Disjoint Gender Masked Face Verification (BCADGMDV vs. CADGMDV).

BCAJGMDV vs. CAJGMDV: To compare joint effect of gender and aging with mask and no-mask, we used same 1:1 cross-age verification strategy as in (BCADGMDV vs. CADGMDV) but with joint gender. We named this cross-age protocol as Baseline Cross-Age Joint Gender No-Masked Face Verification vs. Cross-Age Joint Gender Masked Face Verification (BCAJGMDV vs. CAJGMDV).

BCANMDG&MDPI vs. CANMDG&MDPI and BCANMDG&NDPI vs. CANMDG&NDPI: This protocol simulates two real time identification cases: (i) time of re-opening school and (ii) missing child recognition in pandemic. In former case, the gallery set faces were with no-mask and the probe set faces were with mask. We perform cross-age identification comparison between all gallery enrollment samples of all subjects and probe non-enrollment samples. Particularly, we conduct joint gen-

Fig. 2: Pipeline for generating face mask dataset.

Fig. 3: Four protocols of child longitudinal study with and without mask (zoom for better view).
### Table 2: Longitudinal verification rate (%) of considered face recognition systems on disjoint gender without mask.

| Model       | Boys                  | Girls         |
|-------------|-----------------------|---------------|
|             | ΔT1 | ΔT2 | ΔT3 | ΔT4 | ΔT5 | ΔT6 | Avg | ΔT1 | ΔT2 | ΔT3 | ΔT4 | ΔT5 | ΔT6 | Avg |
| FaceNet     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 1e−4        | 70.84 | 57.17 | 40.97 | 28.97 | 21.57 | 16.86 | 39.40 | 75.39 | 69.71 | 59.10 | 44.76 | 30.61 | 22.30 | 50.31 |
| PFE         |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 1e−4        | 99.80 | 99.58 | 98.48 | 94.55 | 92.60 | 86.39 | 95.23 | 99.69 | 99.33 | 99.28 | 98.94 | 96.55 | 94.23 | 98.00 |
| ArcFace     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 1e−4        | 99.64 | 99.46 | 99.03 | 97.41 | 95.19 | 92.01 | 97.12 | 99.69 | 99.37 | 99.40 | 99.13 | 96.55 | 94.92 | 97.68 |
| COTS        |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 1e−4        | 99.97 | 99.80 | 99.62 | 99.52 | 99.52 | 97.92 | 99.21 | 99.69 | 99.42 | 99.54 | 99.13 | 97.90 | 96.51 | 98.69 |
| Avg         |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
|             | 92.88 | 88.17 | 83.62 | 71.75 | 67.94 | 68.93 | 80.79 | 93.97 | 91.85 | 89.15 | 84.92 | 79.28 | 72.48 | 85.24 |

### Table 3: Longitudinal verification rate (%) of considered face recognition systems on disjoint gender with mask.

| Model       | Boys                  | Girls         |
|-------------|-----------------------|---------------|
|             | ΔT1 | ΔT2 | ΔT3 | ΔT4 | ΔT5 | ΔT6 | Avg | ΔT1 | ΔT2 | ΔT3 | ΔT4 | ΔT5 | ΔT6 | Avg |
| FaceNet     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 1e−3        | 57.14 | 44.65 | 30.72 | 23.41 | 18.52 | 13.81 | 31.04 | 66.33 | 57.83 | 50.51 | 43.23 | 31.31 | 27.05 | 46.23 |
| PFE         |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 1e−3        | 94.37 | 89.38 | 80.07 | 69.83 | 59.50 | 52.85 | 74.40 | 96.77 | 93.90 | 92.12 | 88.78 | 71.83 | 74.80 | 87.37 |
| ArcFace     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 1e−3        | 97.32 | 94.72 | 89.57 | 83.54 | 75.40 | 67.86 | 84.76 | 98.82 | 94.96 | 93.85 | 91.26 | 87.91 | 83.46 | 92.24 |
| COTS        |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 1e−3        | 97.95 | 96.01 | 91.87 | 88.07 | 86.88 | 85.54 | 91.05 | 97.94 | 98.16 | 97.88 | 96.30 | 91.21 | 92.88 | 96.01 |
| Avg         |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
|             | 77.55 | 70.33 | 59.82 | 49.28 | 45.22 | 40.97 | 57.20 | 82.28 | 79.02 | 73.30 | 68.39 | 59.35 | 54.71 | 69.51 |

### 4. EXPERIMENTAL RESULTS

We present the cross-age verification, cross-age identification, and verification performance achieved by the four FRS.

#### 4.1. BCADGNMDV vs. CADGMDV

In Table 2, we report results of longitudinal verification rate of face recognition systems with gender disjoint and without mask. Several observations can be obtained from Table 2. For instance, at 0.1% FAR operating point, the average accuracy over ΔT1 to ΔT6 for boys ranges from 57.64% (by FaceNet) to 99.21% (by COTS).

Whereas, it ranges from 70.77% (by FaceNet) to 98.69% (by COTS) for girls. As the age lapse between gallery and probe samples increases, the accuracy of face systems decreases, e.g., the COTS verification rates with 0.01% FAR operating point for boys are 99.72% at ΔT1 and 95.26% at ΔT6. Based on majority voting, we can state that all considered face systems achieved better performances for girls than boys under all-time lapses. For example, the average accuracies with 0.01% FAR operating point of boys and girls at ΔT3 are 83.62% and 89.15%, respectively. Similar face systems’ bias towards girls/females was reported in [4]. Moreover, we analyzed the skin tones of boys and girls by selecting a 3 × 3 patch from forehead of the subject, then we averaged the patch values as a skin tone indicator. The average skin tone indicator for boys and girls, in the used dataset, is 166.07 and 176.59, respectively. Namely, the girls’ skin tones are lighter than boys, and it has been reported in many studies, e.g., [17], that face systems attain better performances on lighter skin subjects. Also, we found that more boy subjects are with eyeglasses than girls that may be another variate negatively impacting the face systems. Among FaceNet [5], PFE [18], ArcFace [19] and COTS face systems [20], COTS outperformed others consistently for all time lapses. However, among three academic face systems, FaceNet and ArcFace, respectively, achieved worst and best performances, because FaceNet uses softmax loss function which is known for not being capable of discriminating hard pairs [19]. Whereas, ArcFace is based on additive angular margin loss that simultaneously enhances the intra-class compactness and inter-class discrepancy. Similar observations can be seen in Table 3 for CADGMDV experiment. Besides, we can notice in Tables 2 and 3 that face mask decreases the performances of face systems. For example, the average verification rates at 0.1% FAR operating point using PFE for girls without and with mask, respectively, are 98.0% and 87.37%. Also, it is evident that face mask with aging leads to a greater performance degradation than only with mask, e.g., for boys without mask, the average verification rate with 0.01% FAR operating point at ΔT1 is 92.38%, while it is 40.97% with mask at ΔT6.

#### 4.2. BCAGJMDV vs. CAJGMDV

Table 4 shows the results of joint gender when both probe and gallery samples are without mask (‘Boys and Girls with
Table 4: Longitudinal verification rate (%) of face recognition systems on joint gender with and without mask.

| Protocol | Boys and Girls with No-Mask | Boys and Girls with Mask |
|----------|-----------------------------|--------------------------|
| Model    | F1  | T1  | T2  | T3  | T4  | T5  | T6  | Avg  | F1  | T1  | T2  | T3  | T4  | T5  | T6  | Avg  |
| FaceNet  |     |     |     |     |     |     |     |      |     |     |     |     |     |     |     |      |
| 1e-4     | 77.08 | 65.55 | 52.20 | 39.54 | 26.85 | 25.25 | 47.75 | 55.19 | 53.20 | 66.11 |
| PFE      |     |     |     |     |     |     |     |      |     |     |     |     |     |     |     |      |
| 1e-4     | 99.76 | 99.28 | 99.03 | 98.55 | 98.64 | 98.39 | 96.91 | 98.31 | 98.02 | 97.52 |
| ArcFace  |     |     |     |     |     |     |     |      |     |     |     |     |     |     |     |      |
| 1e-4     | 93.78 | 99.60 | 97.57 | 96.08 | 96.55 | 90.48 | 95.82 | 96.57 | 98.75 | 97.93 |
| COTS     |     |     |     |     |     |     |     |      |     |     |     |     |     |     |     |      |
| 1e-4     | 99.84 | 99.73 | 99.65 | 99.32 | 97.94 | 97.48 | 98.99 | 98.63 | 97.55 | 91.32 |
| Avg      | 94.02 | 90.80 | 86.96 | 82.10 | 76.22 | 72.69 | 83.79 | 80.07 | 75.70 | 68.35 |

No-Mask') and when both probe and gallery samples are with mask ('Boys and Girls with Mask'). It can be seen in Table 4 that the performances of the systems are optimal when the acquisition time delay between probe and gallery is small (i.e., time lapse T1). Also, the face systems attained lower cross-age verification performance when both probe and gallery samples are with mask than when both probe and gallery samples are without mask.

Table 5: Longitudinal closed-set identification rate (%) of joint gender face recognition systems on (gallery vs. probe) no-mask vs. no-mask, no-mask vs. mask and mask vs. no-mask.

| Protocol | Model | Rank | No-mask vs. No-mask | No-mask vs. Mask | Mask vs. No-mask |
|----------|-------|------|---------------------|------------------|-----------------|
|          |       |      | F1  | T1  | T2  | T3  | T4  | T5  | T6  | Avg  | F1  | T1  | T2  | T3  | T4  | T5  | T6  | Avg  |
| FaceNet  |       | (2)  |     |     |     |     |     |     |     |      |     |     |     |     |     |     |     |      |     |
| R-1      | 95.49 | 94.11 | 91.80 | 90.32 | 87.14 | 87.16 | 91.01 | 76.40 | 73.66 | 70.98 | 67.59 | 64.40 | 67.80 | 70.17 | 79.18 | 64.85 |
| PFE      |       | (0)  |     |     |     |     |     |     |     |      |     |     |     |     |     |     |     |      |     |
| R-1      | 93.81 | 94.01 | 91.12 | 89.62 | 87.61 | 81.20 | 68.61 | 70.18 | 68.20 | 59.66 | 24.25 | 28.46 | 28.11 | 20.97 | 19.72 | 22.65 | 22.71 | 21.06 | 24.53 | 24.31 |
| ArcFace  |       | (1)  |     |     |     |     |     |     |     |      |     |     |     |     |     |     |     |      |     |
| R-1      | 99.83 | 97.38 | 97.50 | 96.82 | 97.18 | 97.51 | 98.28 | 97.97 | 97.38 | 98.42 | 98.25 | 98.75 | 98.02 | 98.28 | 98.43 | 98.25 | 98.28 | 98.75 | 98.25 |
| COTS     |       | (3)  |     |     |     |     |     |     |     |      |     |     |     |     |     |     |     |      |     |
| R-1      | 99.83 | 97.38 | 97.50 | 96.82 | 97.18 | 97.51 | 98.28 | 97.97 | 97.38 | 98.42 | 98.25 | 98.75 | 98.02 | 98.28 | 98.43 | 98.25 | 98.28 | 98.75 | 98.25 |

Table 6: Verification rate (%) of disjoint gender face systems on no-mask with eyeglasses and mask with eyeglasses.

| Protocol | No-mask vs. Mask | No-mask vs. No-mask | Mask vs. No-mask | FaceNet | PFE | ArcFace | COTS |
|----------|------------------|---------------------|-----------------|---------|-----|---------|------|
| Model    | F1  | T1  | T2  | T3  | T4  | T5  | T6  | Avg  | F1  | T1  | T2  | T3  | T4  | T5  | T6  | Avg  |
|          |     |     |     |     |     |     |     |      |     |     |     |     |     |     |     |      |
| No-mask+ Eyeglass |     |     |     |     |     |     |     |      |     |     |     |     |     |     |     |      |
| Boys     | 68.70 | 48.90 | 39.34 | 36.55 | 10.90 | 99.77 | 99.88 | 99.60 | 86.17 |     |     |     |     |     |     |      |
| Girls    | 81.83 | 80.57 | 79.47 | 78.34 | 14.90 | 97.98 | 99.90 | 99.73 | 89.12 |     |     |     |     |     |     |      |
| Mask+ Eyeglass |     |     |     |     |     |     |     |      |     |     |     |     |     |     |     |      |
| Boys     | 72.29 | 71.85 | 70.82 | 69.45 | 39.04 | 97.39 | 99.92 | 99.71 | 85.99 |     |     |     |     |     |     |      |
| Girls    | 99.07 | 97.58 | 97.05 | 96.55 | 97.56 | 97.47 | 97.44 | 97.42 | 1.88 |     |     |     |     |     |     |      |

4.4. BENMDGV vs. EMDGV

The objective of this experiment is to study gender bias with eyeglasses and mask on verification. Out of 26,258 images in ECLF dataset, only 1,718 images from 396 boy and 346 girl subjects are with eyeglasses. For fairness, we selected 2,222 subjects for each boy and girl group, where 88 subjects are with 2 images, 70 with 3 images, 46 with 4 images and 18 with 5 images. We can observe in Table 6 that even though boys and girls subjects are with eyeglasses but for girls the FRS achieved higher performances in both no-mask+eyeglass (i.e., both template and query are without mask) and mask+eyeglass (i.e., both template and query are with mask) setting. For example, COTS procured 99.60% and 100% (for no-mask) and 91.28% and 94.42% (for mask) at FAR 0.01% for boys and girls, respectively. It is also easy to see that mask+eyeglasses lessen the accuracies of the FRS, e.g., FaceNet accuracy diminished from 68.70% to 27.20% for boys. For eyeglass+(no-) mask, COTS performed better than ArcFace.

5. CONCLUSION AND FUTURE WORK

Driven by the COVID-19 pandemic and subsequent face mask conformity, this paper, contrary to prior works, investigated the impact of aging with face mask on child subject recognition. Particularly, the empirical efficacy of four FRS was conducted under face mask children cross-age verification and identification scenarios. This study assembled longitudinal Indian children (i.e., boys and girls aged from 2 to 18) cohorts database with synthetic masks, and showed that face systems’ performances are severely deteriorated by aging with masks. Moreover, the study found that accuracy of FRS is affected by mask with eyeglasses. Also, the identification levels of girls in the ECLF appear to be higher than boys. In future, we will work towards creating a longitudinal child database with real masks and different ethnicities, developing FRS that are inherently robust to face mask aging, and investigating face mask aging as a face presentation attack.
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