What is my Name?

Kashyap Nirmal
DAIICT
Gandhinagar, India
Email : 202011031@daiict.ac.in

Supervisor : Manish K. Gupta
Email : mankg@guptalab.org

***Abstract*—This report introduces a new concept of predicting the first name from the facial image. The prediction problem here is treated as a classification problem. We have used two datasets here. Both the dataset mentioned here have no additional labelling cost apart from the name tags freely available on the internet. Dataset Name100 consists of 100 popular names of the U.S. We created a custom dataset for Indian faces. The Indian dataset contains of 5 Indian names. Several studies show a relationship between first names and facial features. Despite such a system's low accuracy and imperfectness, the prediction was correct at rates that were greater than chance.**

***Index Terms*—First name, facial image, classification.**

I. Introduction

Suppose a person meets a new face. They have several questions in their mind. Who are they? (i.e., First Name). How old are they? (i.e., Age). Where are they based? (i.e., Ethnicity in a more general way). What is their gender? What is their occupation? Even one can think of the emotions of the other person. Also, consider a similar scenario for the image of a new face. So consider the above mentioned as features we can extract from a facial image.

The human brain can predict some of these attributes through a glance. It can predict gender in almost all cases. It can also predict the age group. Predicting exact age can be a bit difficult, though. Through some other facial features, it can also predict certain races. Not from the face, but at times may be through the clothing, some occupations can also be predicted. It can also predict happiness or sadness or some other emotions on a face. So, from the above-mentioned features predicting the first name can be new. Also, nearly impossible.

Every individual has a faceprint [1]. It's an electronically stored portrayal of a person's face that's as unique as a fingerprint. So it may have applications for security purposes.

The human face has facial landmarks. For instance, eyes, nose, ears, lips etc., can be described through these landmarks. These landmarks are used in face recognition. These face recognition systems can be used for face unlock features. A few years back, a case where the face unlock of a mobile device failed to differentiate two twins was found. So a potential solution of differentiating twins with the landmarks of the tip of the ears was found. These landmarks can also be used for expression or emotion detection.

Parents expecting a baby, mostly spends a great amount of time deciding on the name of the child. Most of the times it maybe assumed that the choice of the name is nearly random from a vast pool of names [2]. Does there exist any relationship between the first name of the person and the facial image? Mostly if people are posed with the question, they would deny. But there are several studies that indicate the existence of a relationship.

Shakespeare states, "What's in a name?" and might proclaim it to be either insignificant or random. Nonetheless, a growing amount of study examines the relationship of our names and who we are (Krammer et al., 2015, p. 2) [3].

The focus is on first names and not on the last names because the former one illustrates more freedom and variety when selecting. At the same time, the latter tends to be determined more by lineage or, in some cases, based on occupation. Rather than arbitrariness, clear patterns have been observed between the owner and the name. In general names are mostly gender specific. Even though very few names are gender-neutral like Jamie. Even the education of the parents' and their race does influence the choices of names. Names do carry the information about the age because trends in naming keep on varying throughout decades. (Krammer et al., 2015, p. 2) [3].

One of the potential applications of name prediction is name association. Suppose, for instance, we are given a group photograph, and we know the name of the people present there. So using this system, one can associate the name to the face. Like in various social media platforms like Facebook and Instagram, people post images and tag other users. So, the system can associate the name to the face. This thing is already present in these social media, but still, there may be some scope of improvement in that.

The remainder of the report includes the following. The second section here includes the problem Statement. The third section describes Literature Survey. The fourth section provides information regarding the dataset we plan to use. The fifth section proposes future work. The sixth section concludes the report. And then, the report ends with references.

II. Problem Statement

Predict the first name of a person from the facial image of the person. The problem here is assumed to be a classification problem. The Classification problem means identifying a category from the available classes. The system predicts the class label which accommodates the new training sample. This task is supervised learning as the class labels are predefined. Thus the final output label will also be from the same set of these class names used in the dataset.

III. Related Work

According to [4] (as cited in [2]) the achievements of face detection and recognition in computer vision have been found dating back to approximately four decades.

This work poses as well as thus starts to solve a unique topic in facial processing. Is it possible to infer a person's name from through a single facial image? While that too, without additional sample images of such face. Expecting a high level of accuracy from this work is impractical. However, the identical twins get their unique names. This flawed system could have a variety of usages, for instance, in terms of security and biometrics. In the security aspect, finding fake IDs from databases can be solved using this system. And for biometrics, we can infer the ethnicity, sex, age by taking a guess of probable names from a face [2].

A variety of aspects influences the name selection. The gender of the individual can control the name selection. Even the age, race, social culture, economic culture, the popularity of names, names of near and dear also influence name selection. Thus, even within an ethnicity, the occurrence of particular first names varies. There is a significant age difference in easily distinguishable name pairs. The name pairs which exhibit the same popularity trends seem indistinguishable [2].

The visual characteristics that distinguish any given set of people differ. First names and numerous face aspects contain a relationship. According to [5] (as cited in [2]), aspects such as skin colour, male-ness, facial feature size, age, and potentially other unnamed traits correlate with first names. Now, for instance, the genders of "David" and "Mary" vary. At the same time, the names "David" and "Ethan" are distinguished primarily in age because "Ethan" is a newer name [2].

Danny has a boyish appearance and a permanent smile in someone's imagination. Zoe has big eyes, wild hair, as well as a mildly amused demeanour. According to studies, the concept that persons with the same name have the same typical "look" can be genuine. A study was released in the Journal of Personality and Social Psychology. Here the researchers offered an unfamiliar face that had five choices of names. And the individuals selected the correct name for around thirty-five per cent of the cases. In contrast, the probability is only twenty per cent [6].

They showed a face with ten alternative names because it seemed highly unreasonable to expect a person to choose one name from a list of the 100 names. The names in this list here include nine arbitrary names of the same sex in a randomized fashion and one correct name. The correctness of human predictions is thirteen point seven per cent, which is much better than the chance of ten per cent [2]. The researchers never claimed that this can be carried out by anyone anywhere without having any cultural familiarity.

Individuals having the same name are prone to having almost identical expressions around the mouth and the eye area of the face. These areas seem easily adjustable, as per a computer analysis [6].

The classifier was trained with the facial image obtained over the internet. The output values are significantly higher than the probability. Thus, the system accurately predicts the actual first name of research subjects. There was no extra user intervention in training. First names are not distributed arbitrarily among society's members [2].

IV. Dataset

A. Name100

Name100 is the first dataset with Name and Face data. They create an extensive dataset by choosing images and tags from Flickr to determine the connection between first name and facial appearance. The dataset comprises 800 faces, for each of the 100 most famous first names, based on information from the U.S. Social Security Administration (SSA) [7] (as cited in [2]). After completion, the dataset contains 48 men's names, 48 women's names, and 4 gender-neutral names. The names listed represent 20.35 per cent of all the Americans birthed from 1940 to 2010 [2].

When there are numerous people in a photo, name ambiguity occurs. Thus, images that contained multiple faces were eliminated, and it was verified whether the image tag included exactly one first name tag. Secondly, they removed the images that had celebrity names. The reason being this can result in a bias in their sampling. Assume that a search for "Brad" could produce a lot of photographs of the film actor "Brad Pitt," distorting the facial feature pattern for the name "Brad" [2].

Fig. 1. Sample of Alejandra's facial images from Name100 dataset [2]

Here figure 1 shows Alejandra's face examples. Similarly, figure 2 and figure 3 shows Heather's and Ethan's face examples respectively. Alejandra's hair and skin are usually darker unlike Heather's. The name Ethan, which gained popularity in recent years, appears to be much young. Along these lines going a step further, for instance, the predominance of specific first names varies amongst a race.

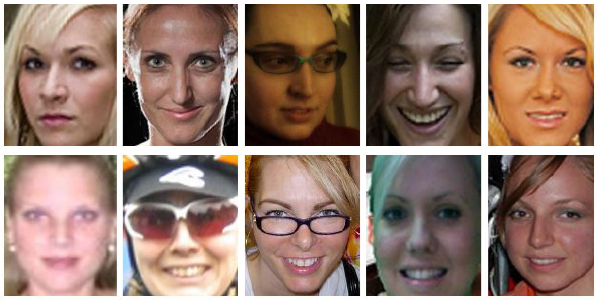

Fig. 2. Sample of Heather's facial images from Name100 dataset [2]

Fig. 3. Sample of Ethan's facial images from Name100 dataset [2]

B. *Indian Dataset*

We have created a dataset on Indian faces. Here, we tried collecting data from Google form. However, there was a lesser number of responses than we expected. We have also scrapped the data from LinkedIn. The dataset comprises five classes with 180 images of each class. Thus in total, this dataset has 900 images. The preprocessing was done using OpenCV.

Here we have considered five first names. We have divided them into two male names, two females names and one gender-neutral name. Here mainly, the first name Krishna is gender-neutral.

Here figure 4 shows Krishna's face examples from the dataset. Similarly, figure 5 shows Pranav's face examples.

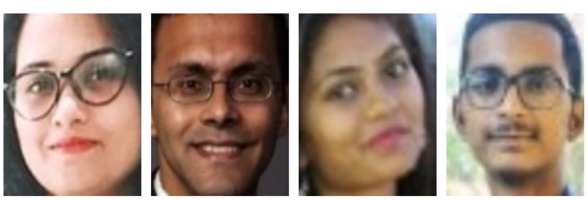

Fig. 4. Sample of Krishna's facial images from Indian dataset.

Fig. 5. Sample of Pranav's facial images from Indian dataset.

V. Results and Experiments

We have implemented various algorithms. We have implemented Vision Transformer [8], ensemble learning like Bagging [9] , and boosting algorithms like Adaboost [10] and XGBoost [11]. For extracting features, we have used Spatial pyramid pooling [12] and Deep Learning features. For Deep learning, it uses the Relu activation function.

In Spatial pyramid pooling [12], algorithm 21 features are extracted in 3 levels. In Level 0, the image is undivided. In Level 1, the image is divided into 4 regions, and 4 features are extracted here. The Level 3 image is divided into 16 regions, and 16 features are extracted here. Thus these concatenated 21 features are used in classification .

A. *Vision Transformer*

Vision transformer [8] is the state of the art for image classification for ImageNet. And we applied this model and were able to achieve higher accuracy for a certain set of classes. This model has various variations. We have used ViT_B_16 with the image resolution of 224 x 224, and it was trained on the Imagenet21k dataset. Here B stands for Base. 16 are the number of patches.

B. *Ensemble Learning*

The ensemble learning technique combines various weak learners to achieve higher prediction accuracy. These weak learners can be any classifier algorithm. Some of the commonly used learners are Random forests. A few of the commonly used Ensemble learning techniques are bagging and boosting.

In the bagging technique [9], all the classifiers learn independently and parallelly. The results of all these classifiers are combined to determine the final output.

In boosting technique, classifiers are used in an iterative manner. After each iteration, the weights for the misclassified samples are increased, and the weights for the correctly classified samples are decreased. This is done in order to provide more importance to the misclassified samples. And thus, it learns from its previous mistakes. XGBoost [8] and AdaBoost [10] are boosting algorithms.

TABLE I
RESULTS OF OUR EXPERIMENT. THE NUMBERS REPRESENT THE ACCURACY.THE MODELS WHERE THE ACCURACY NUMBERS ARE HIGHER THAN THE BASELINE HAVE BEEN REPRESENTED IN BOLD.

Sr. No.	Model	Name100 Subset 1	Name100 Subset 2	Indian
1	ViT [8]	35%	**44.2%**	**41.67%**
2	Bagging SPP	35.63%	37.38%	**42.2%**
3	Adaboost SPP	34.63%	37.38%	**41.6%**
4	XGBoost SPP	32.75%	37.25	**44.44%**
5	Adaboost DL	27.5%	31.62%	**39.44%**
6	Bagging DL	29.67%	31.62%	**39.44%**

In the table I prefix SPP stands for Spatial pyramid pooling. These algorithms have used SPP for feature extraction. While the suffix DL stands for Deep learning feature.

Here we have treated MFSVM [2] as the baseline. MFSVM uses boosting technique AdaBoost [10] with the classifier SVM. The baseline for five classes is 39.4%. The random chances for five classes would be one-fifth, i.e. 20%. With ViT model, we have achieved higher accuracy than this baseline for certain subsets of the dataset. While for 10 classes, the baseline of MFSVM is 23.5%. At the same time, the random chances for 10 classes are one-tenth, i.e., 10%. And with ViT for certain subsets of the dataset, it achieves an accuracy of 26%.

Name100 subset 1 stands for classes Chris, Jamie, Maggie, Stephen, and Tina. So the distribution of this subset includes 2 male names, 2 female names and 1 gender-neutral name.

Name100 subset 2 stands for classes Abby, Amanda, Angela, Aaron, and Andrea. So the distribution of this subset includes 1 male name, 4 female names. From figure we can see that Andrea is highly misclassified as Aaron. The name Andrea has Greek origin, and it means "strong and manly". Andrea in the US is used as a female name. But in its native, it is used as a gender-neutral name in Italy and other European nations. And the name Andrea was highly misclassified as Aaron in many other models as well. This is not true for all the models, but yes, it is true for the majority of these models.

However, we achieved an almost higher accuracy score than the random chances with our experiments. Moreover, in some cases, the accuracy score even exceeded the baseline. We have also added the confusion matrix for the models with the highest accuracy for that particular dataset.

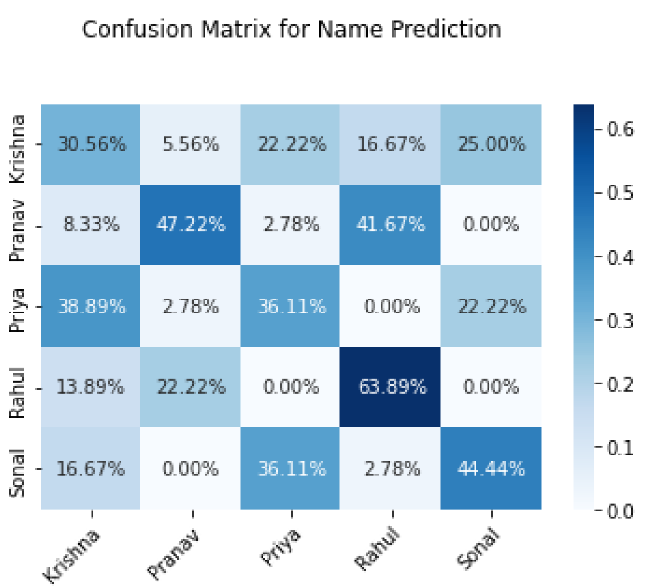

Fig. 6. Confusion matrix for Indian Dataset on XGBoost SPP model. The overall accuracy is 44.44% here.

From the figure 6, we can see that Pranav is majorly misclassified as Rahul. Moreover, Rahul is highly misclassified as Pranav. A male first name is mostly misclassified as other male names instead of female names. Similarly, we can see the results for Priya and Sonal too. The female names

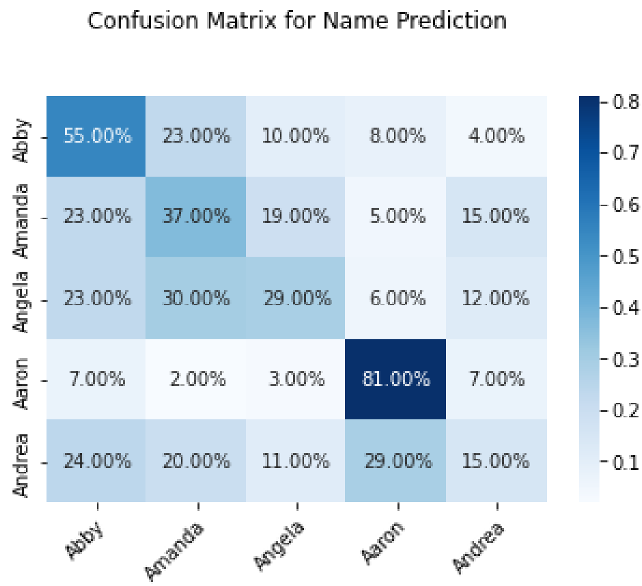

Fig. 7. Confusion matrix for Name100 Dataset for 5 classes Subset 2. The overall accuracy is 44.12% here.

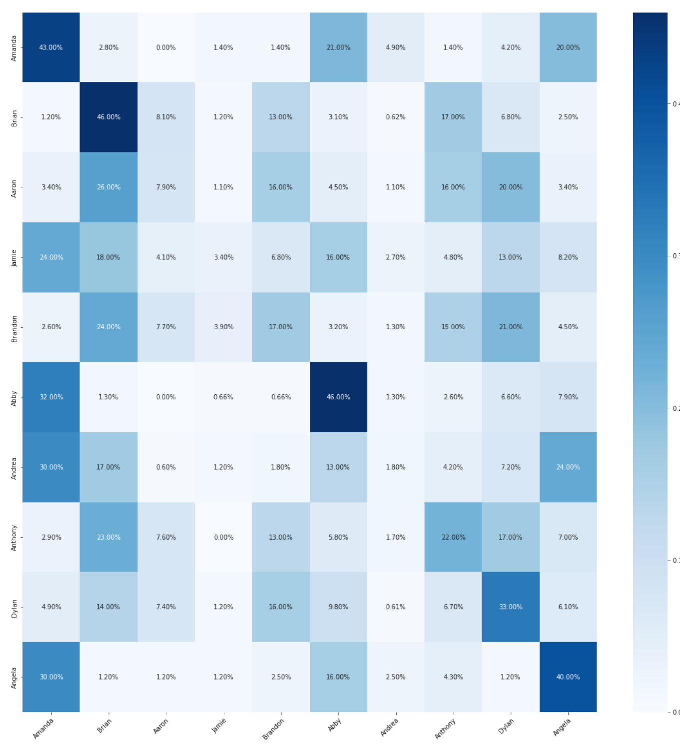

Fig. 8. Confusion matrix for Name100 Dataset for 10 classes. The overall accuracy is 26%.

are highly misclassified as other female names than male names. However, for the gender-neutral name Krishna, it is nondeterministic. Here the overall accuracy is majorly higher than the random chances with some exceptions.

Moreover, from the results of other experiments, a pattern was followed. The first name is mainly misclassified among the first names of same-gender itself. Male names are majorly misclassified into male names only. Rarely for some classes and some models, there can be some exceptions.

VI. Conclusion

In the discipline of computer vision, name prediction can be a tough and inspiring problem to solve. This work did not receive that much consideration and had very restricted efforts in terms of research. The name prediction system is not ideal for functioning well in all real-world situations. The report summarises the results of the experiments that were conducted. We have also constructed the dataset for Indian faces. And with our experiments, we concluded that the patterns found in the Names100 dataset can also nearly be seen in Indian faces. Thus the current works have high prediction accuracy than random chance. The classes with gender-neutral names would require certain amount of future efforts to increase the prediction accuracy. But still plenty of work needs to be carried out to achieve higher efficiency and accuracy goals.

VII. Future Works

We would want to expand the size of the custom Indian dataset. We want to increase the number of classes, i.e. various unique first names. Moreover, we would like to increase the number of image samples per class. We also would like to see and verify if this pattern exists for datasets of other nationalities. We would also like to improve the overall classification accuracy. And we would specifically like to increase the prediction accuracy for gender-neutral classes.

References

[1] Faceprint definition & meaning. [Online]. Available: https://www.dictionary.com/browse/faceprint

[2] H. Chen, A. Gallagher, and B. Girod, "What's in a name? first names as facial attributes," *Proceedings / CVPR, IEEE Computer Society Conference on Computer Vision and Pattern Recognition. IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 3366–3373, 06 2013.

[3] R. Kramer and A. L. Jones. (2015) Do people's first names match their faces? [Online]. Available: https://www.jasnh.com/pdf/Vol12-No1-article1.pdf

[4] T. Kanade, T. Sakai, M. Nagao, and Y. ichi Ohta, "Picture processing system using a computer complex," *Computer Graphics and Image Processing*, vol. 2, no. 3, pp. 207–215, 1973. [Online]. Available: https://www.sciencedirect.com/science/article/pii/0146664X73900026

[5] D. Parikh and K. Grauman, "Interactively building a discriminative vocabulary of nameable attributes," in *CVPR 2011*, 2011, pp. 1681–1688.

[6] A. Chen. (2017) Your name might shape your face, researchers say. [Online]. Available: https://www.npr.org/sections/health-shots/2017/02/27/517496915/your-name-might-shape-your-face-researchers-say

[7] U.s. social security administration baby name database. [Online]. Available: http://www.ssa.gov/oact/babynames

[8] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, and N. Houlsby, "An image is worth 16x16 words: Transformers for image recognition at scale," *CoRR*, vol. abs/2010.11929, 2020. [Online]. Available: https://arxiv.org/abs/2010.11929

[9] L. Breiman, "Bagging predictors," *Machine learning*, vol. 24, no. 2, pp. 123–140, 1996.

[10] T. Hastie, S. Rosset, J. Zhu, and H. Zou, "Multi-class adaboost," *Statistics and its Interface*, vol. 2, no. 3, pp. 349–360, 2009.

[11] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, ser. KDD '16. New York, NY, USA: ACM, 2016, pp. 785–794. [Online]. Available: http://doi.acm.org/10.1145/2939672.2939785

[12] K. He, X. Zhang, S. Ren, and J. Sun, "Spatial pyramid pooling in deep convolutional networks for visual recognition," *CoRR*, vol. abs/1406.4729, 2014. [Online]. Available: http://arxiv.org/abs/1406.4729