Multi-label Classification of Common Bengali Handwritten Graphemes: Dataset and Challenge

Samiul Alam[1, 2], **Tahsin Reasat**[1], **Asif Shahriyar Sushmit**[1], **Sadi Mohammad Siddiquee**[1], **Fuad Rahman**[3], **Mahady Hasan**[4], **Ahmed Imtiaz Humayun**[1]
[1]Bengali.AI, [2]Bangladesh University of Engineering and Technology, [3]Apurba Technologies Inc., [4]Independent University, Bangladesh

Abstract

Latin has historically led the state-of-the-art in handwritten optical character recognition (OCR) research. Adapting existing systems from Latin to *alpha-syllabary* languages is particularly challenging due to a sharp contrast between their orthographies. The segmentation of graphical constituents corresponding to characters becomes significantly hard due to a cursive writing system and frequent use of diacritics in the alpha-syllabary family of languages. We propose a labeling scheme based on *graphemes* (linguistic segments of word formation) that makes segmentation inside alpha-syllabary words linear and present the first dataset of Bengali handwritten graphemes that are commonly used in an everyday context. The dataset is open-sourced as a part of the *Bengali.AI Handwritten Grapheme Classification Challenge* on Kaggle to benchmark vision algorithms for multi-label grapheme classification. From competition proceedings, we see that deep learning methods can generalize to a large span of uncommon graphemes even when they are absent during training. Dataset and starter codes at `kaggle.com/c/bengaliai-cv19`.

1 Introduction

Speakers of languages from the alpha-syllabary or *Abugida* family comprise of up to 1.3 billion people across India, Bangladesh, and Thailand alone. There is significant academic and commercial interest in developing systems that can optically recognize handwritten text for such languages with numerous applications in e-commerce, security, digitization, and e-learning. In the alpha-syllabary writing system, each word is comprised of segments made of character units that are in phonemic sequence. These segments act as the smallest written unit in alpha-syllabary languages and are termed as *Graphemes* (Fedorova 2013); the term alpha-syllabary itself originates from the alphabet and syllabary qualities of graphemes (Bright 1999). Each grapheme comprises of a *grapheme root*, which can be one character or several characters combined as a conjunct. Root characters may be accompanied by *vowel* or *consonant diacritics*- demarcations which correspond to phonemic extensions. To better understand the orthography, we can compare the English word *Proton* to its Bengali transliteration প্রোটন (Fig. 1). While in English the characters are horizontally arranged according to phonemic sequence, the first grapheme for both Bengali and Devanagari scripts have a sequence of glyphs that do not correspond to the linear arrangement of Unicode characters or phonemes. As most OCR systems make a linear pass through a written line, we believe this non-linear positioning is important to consider when designing such systems for Bengali as well as other alpha-syllabary languages.

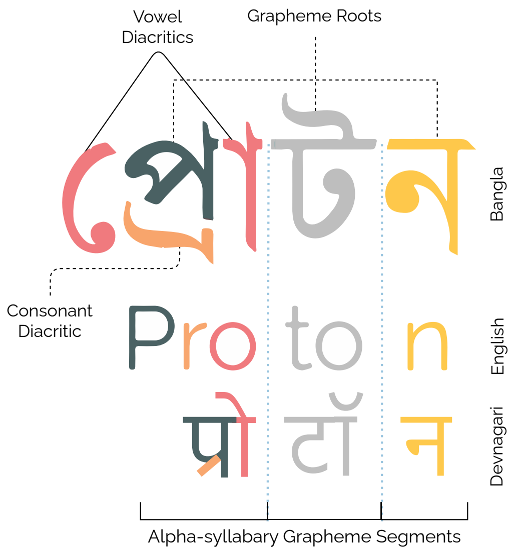


Figure 1: Orthographic components in a Bangla (Bengali) word compared to English and Devnagari (Hindi). The word 'Proton' in both Bengali and Hindi is equivalent to its transliteration. Characters are color-coded according to phonemic correspondence. Alpha-syllabary grapheme segments and corresponding characters from the three languages are segregated with the markers. While characters in English are arranged horizontally according to phonemic sequence, the order is not maintained in the other two languages.

We propose a novel labeling scheme for handwritten Bengali text and based on it, we have curated the

Bengali Handwritten Grapheme Dataset which contains 411882 images of 1295 unique commonly used handwritten graphemes and ∼ 900 uncommon graphemes (exact numbers are excluded for the integrity of the test set). The proposed labeling scheme fundamentally addresses the issues in the past labeling schemes in alpha-syllabary languages and provides an alternate grapheme based approach for Bengali; which can also be extended to other languages. The utilization scope of this dataset is not limited to the domain of OCR; since the dataset has labels for different components of each grapheme, it also creates an opportunity to evaluate multi-task or multi-label classification algorithms.

2 Related Work

Although several datasets (Alam et al. 2018; Biswas et al. 2017; Rabby et al. 2019; Sarkar et al. 2012) have been made for Bengali handwritten characters, their effectiveness has been limited. This could be attributed to the fact that they were formulated following contemporary datasets of English characters. All these datasets label individual characters or words. These datasets work well for English and can even be adapted for other document recognition tasks, setting the standard. Most character recognition datasets for other languages like the Devanagari Character Dataset (Acharya, Pant, and Gyawali 2015; Obaidullah et al. 2016; Dutta et al. 2018) and the Arabic Printed Text Image Database (Farrahi Moghaddam et al. 2010; AlKhateeb 2015) were created following their design. However, they do not boast the same effectiveness and adaptability of their English counterparts. Languages with different writing systems therefore require language specific design of the recognition pipeline and need more understanding of how it affects performance. To the best of our knowledge, this is the first work that proposes grapheme level recognition for Bengali.

3 Challenges of Bengali Orthography

As mentioned before in section 1, each Bengali word is comprised of segmental units called graphemes. Bengali has 48 characters in its alphabet- 11 vowels and 38 consonants (including special characters 'ৎ','ং','ঃ'). Out of the 11 vowels, 10 vowels have diacritic forms. There are also four consonant diacritics, '্য' (from consonant য), '্র' (from consonant র), 'র্' (from consonant র) and 'ঁ'. We follow the convention of considering 'ং','ঃ' as standalone consonants since they are always present at the end of a grapheme and can be considered a separate root character.

3.1 Grapheme Roots and Diacritics

Graphemes in Bengali consist of a root character which may be a vowel or a consonant or a consonant conjunct along with vowel and consonant diacritics whose occurrence is optional. These three symbols together make a grapheme in Bengali. The consonant and vowel diacritics can occur horizontally, vertically adjacent to the root or even surrounding the root (Fig. 2). These roots and diacritics cannot be identified in written text by parsing horizontally and detecting each glyph separately. Instead, one must look at the whole grapheme and identify them as separate labels. In light of this, our dataset labels individual graphemes with root characters, consonant and vowel diacritics as separate labels.

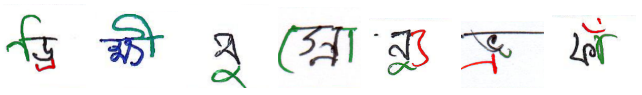


Figure 2: Different vowel diacritics (green) and consonant diacritics (red) used in Bengali orthography. The placement of the diacritics are not dependent on the grapheme root.

3.2 Consonant Conjuncts or Ligatures

Consonant conjuncts in Bengali are analogous to ligatures in Latin where multiple consonants combine together to form glyphs which may or may not contain characteristics from the standalone consonant glyphs. In Bengali, up to three consonants can combine to form consonant conjuncts. Consonant conjuncts may have two (second order conjuncts, eg. ষ্ট = শ + ট) or three (third order conjuncts, eg. ক্ষ্ণ = ক + ষ + ণ) consonants in the cluster. Changes in the order of consonants in a conjunct may result in complete or partial changes in the glyph.

3.3 Allographs

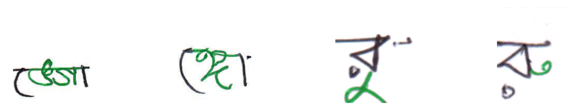

(a) (b) (c) (d)

Figure 3: Examples of allograph pairs for the same consonant conjunct 'ঙ্গ' (3a and 3b) and the same vowel diacritic 'ু' (3c and 3d) marked in green. 3b and 3d follows an orthodox writing style.

It is also possible for the same grapheme to have multiple styles of writing, called allographs. Although they are indistinguishable both phonemically and in their Unicode forms, allographs may in fact appear to be significantly different in their handwritten guise (Fig. 3). Allograph pairs are sometimes formed due to simplification or modernization of handwritten typographies, i.e. instead of using the orthodox form for the consonant conjunct ঙ্গ = ঙ + গ as in Fig. 3b, a simplified more explicit form is written in Fig. 3a. The same can be seen for diacritics in Fig. 3c and Fig 3d. It can be argued that allographs portray the linguistic plasticity of handwritten Bengali.

3.4 Unique Grapheme Combinations

One challenge posed by grapheme recognition is the huge number of unique graphemes possible. Taking into account the 38 consonants (n_c) including three special characters, 11 vowels (n_v) and ($n_c^3 + n_c^2$) possible consonant conjuncts (considering 2nd and 3rd order) there can be $((n_c - 3)^3 + (n_c - 3)^2 + (n_c - 3)) + 3$ different grapheme roots possible in Bengali. Grapheme roots can have any of the 10+1 vowel diacritics (n_{dv}) and 7+1 consonant diacritics (n_{dc}). So the approximate number of possible graphemes will be $n_v + 3 + ((n_c - 3)^3 + (n_c - 3)^2 + (n_c - 3)) \cdot n_{dv} \cdot n_{dc}$ or 3883894 unique graphemes. While this is a big number, not all of these combinations are viable or are used in practice.

4 The Dataset

Of all the possible graphemes combinations, only a small amount is prevalent in modern Bengali. Therefore, we narrowed down the total number of graphemes to reduce the complexity of the dataset.

4.1 Grapheme Selection

To find the popular graphemes, we use the text transcriptions for the Google Bengali ASR dataset (Kjartansson et al. 2018) as our reference corpus. The ASR dataset contains a large volume of transcribed Bengali speech data. The transcription data by itself is very large and well standardized. It consists of 127565 utterances comprising 609510 words and 2111256 graphemes. Out of these graphemes, 1295 commonly used Bengali graphemes in everyday vocabulary is selected. Each candidate grapheme had to occur more than twice in the entire corpus or used in at least two unique words to be selected in our pool. Graphemes from highly frequent transliterations and misspelled words were also considered. The uncommon graphemes were synthesized by uniformly sampling from all the possible combinations and verifying their legibility.

4.2 Labeling Scheme

Bengali graphemes can have multiple characters depending on the number of consonants, vowels or diacritics forming the grapheme. We split the characters of a Bengali grapheme into three labels:

1. Vowel Diacritics, i.e. া, ি, ী, ু, ূ, ৃ, ে, ৈ, ো, ৌ. If the grapheme consists of a vowel diacritic, it is generally the final character in the Unicode string. Graphemes cannot contain multiple vowel diacritics. The vowel diacritic label has 11 orthogonal classes including a null diacritic denoting absence.

2. Consonant Diacritics, i.e. ্য, ্র, ঁ, র্ . Graphemes can have a combination of consonant diacritic characters eg. '্র্য' = '্র' + '্য'. We consider each combination to be a unique diacritic in our scheme for ease of analysis. The consonant diacritic label has 8 orthogonal classes including combinations and a null diacritic.

3. Grapheme roots, which can be comprised of vowels, consonants or conjuncts. In Unicode these are placed as the first characters of a grapheme string. An alternative way of defining grapheme roots would be considering all the characters apart from diacritics as root characters in a grapheme. While possible orthogonal classes under this label can be a very big number (see Section 3.4), we limit the number of consonant conjuncts based on commonality in everyday context.

Grapheme recognition thus becomes a multi-label classification task where a vision algorithm would have to separately recognize grapheme roots, vowel diacritics and consonant diacritics.

4.3 Collection Statistics

Handwritten data is collected using printed template forms each containing upto 81 unique graphemes. Contributors from ages 0 − 50 with diverse educational backgrounds, provided 162 graphemes handwritten graphemes each. After curation, the final dataset contains a total of 411882 handwritten graphemes of size 137 by 236 pixels. Dataset collection tools and protocols are available at `https://rb.gy/lawaoj`.

4.4 Class Imbalance in Dataset

We divide the roots into three groups- vowels, consonants, and consonant conjuncts- and inspect class imbalance within each. There are linguistic rules which constrict the number of diacritics that may occur with each of these roots, eg. vowel roots never have added diacritics. Although imbalance in vowel roots is not major, it must be noted because the relatively infrequent vowel roots 'ঈ', 'ঊ' and 'ঐ' share a close resemblance to the more frequent roots 'ই', 'উ' and এ respectively.

The imbalance in consonant roots is however much more striking as we can see in Fig. 4. The imbalance here is twofold- in the number of total sample images of consonant roots and the imbalances in the distribution of the vowel and consonant diacritics that can occur with each consonant. The consonant conjuncts demonstrate imbalance similar to the consonant roots but with an added degree of complexity. We can visualize this imbalance much better via the chord diagram in Fig. 5. The consonant conjuncts are made up of multiple consonant characters and since the glyph of a consonant conjunct often shares some resemblance with its constituent consonants, highly frequent consonants may increase estimation bias for less frequent conjuncts containing them. This phenomenon is indeed visible and further discussed in Section. 5.3.

5 The Challenge

Of all the samples present in the dataset, 200840 were placed in the training set, 98661 in the public test set, and 112381 in the private test set; while making sure there is no overlap in contributors between sets. Most of the uncommon graphemes were placed in the private test set and none in the training subset. Throughout

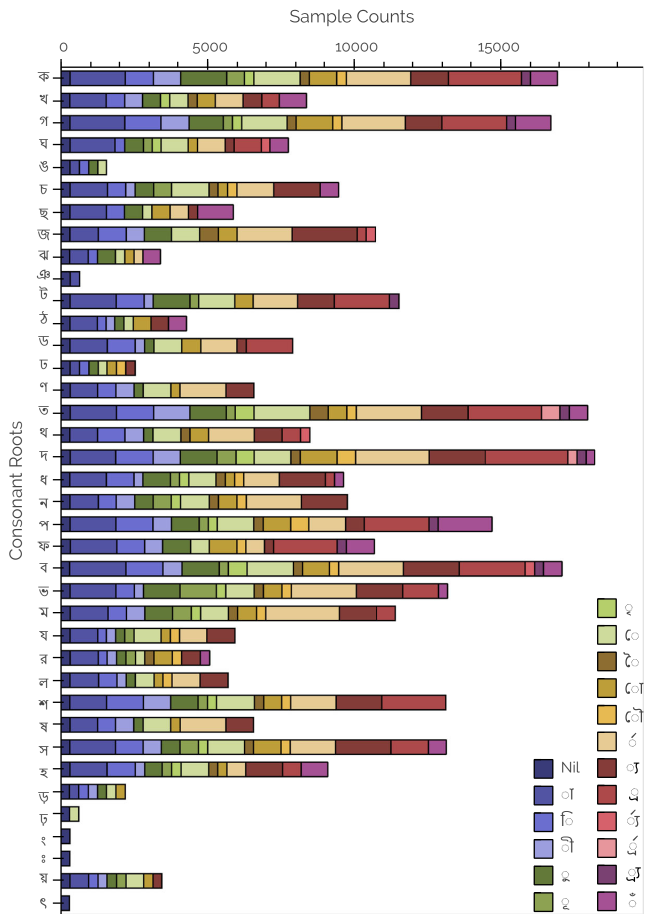


Figure 4: Number of samples per consonant root. Each bar represents the number of samples which contain a particular consonant and the divisions in each bar represent the distribution of diacritics in the samples containing that consonant.

the length of the competition, the participants try to improve their standings based on the public test set results. The private test set result on the other hand, is kept hidden for each submission and is only published after the competition is over. Of the unseen graphemes, 88.4% were placed in the private test set to prevent over-fitting models based on public standings. This motivated the participants to build methods that have the capacity to classify grapheme components independently instead of fine-tuning models based on public test set standings.

5.1 Competition Metric

The metric for the challenge is a hierarchical macro-averaged recall. First, a standard macro-averaged recall is calculated for each component. Let the macro-averaged recall for grapheme root, vowel diacritic, and consonant diacritic be denoted by R_r, R_v, and R_c respectively. The final score R is the weighted average $R = (2R_r + R_v + R_c)/4$.

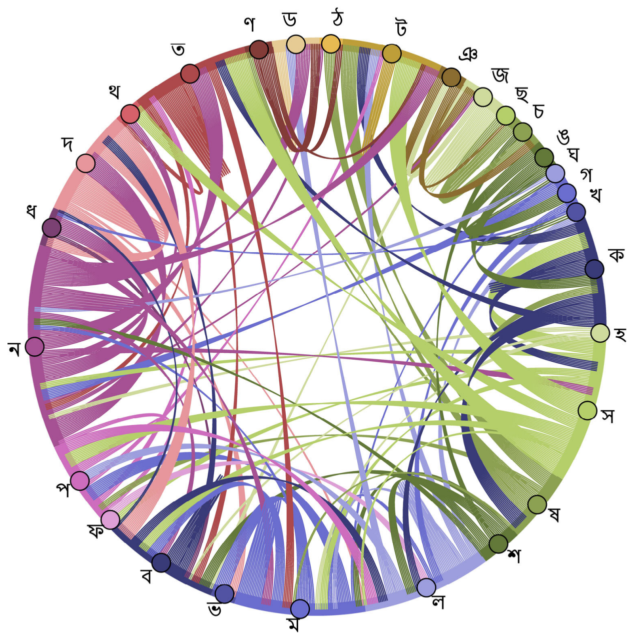


Figure 5: Connectivity graph between consonants forming second-order conjuncts. The length of each arc shows how often the consonant occurs as a consonant conjunct. Higher frequency of consonants in (eg. ক) may bias lower frequency conjuncts towards the constituent.

5.2 Top scoring methods

The Kaggle competition resulted in 31,002 submissions from 2,059 teams consisting of 2,623 competitors. The participants have explored a diverse set of algorithms throughout the competition; the most popular being state of the art image augmentation methods such as cutout (DeVries and Taylor 2017), mixup (Zhang et al. 2017), cutmix (Yun et al. 2019), mixmatch (Berthelot et al. 2019) and fmix (Harris et al. 2020). Ensemble methods incorporating snapshots of the same or different network architectures were also common.

The *winner* took a grapheme classification approach rather than component recognition. The input images were classified into 14784 (168 x 11 x 8) classes, that is, all the possibles graphemes that can be created using the available grapheme roots and diacritics. An EfficientNet (Tan and Le 2019) model is initially used to classify the graphemes. However, if the network is not confident about its prediction then the sample is considered as an unseen grapheme and it is passed on to the unseen grapheme classification pipeline. The pipeline consists of a CycleGan (Zhu et al. 2017) that is trained to convert handwritten graphemes into typeface rendered graphemes. An EfficientNet classifier trained on a 14784 class synthetic grapheme dataset is used as an unseen grapheme classifier.

The *second* place team also built their solution upon a grapheme classifier, but the number of classes were limited to the 1295 unique graphemes in training. A post processing heuristic is employed to generalize for any unseen graphemes. For each class in a component (eg. consonant diacritic 'র্'), probabilities of all the unique graphemes in training containing the component class are averaged. This is repeated for every class for a component and the class with the highest average probability is selected. Architectures used are different variants of SE-ResNeXt (Hu, Shen, and Sun 2018).

The *third* placed team dealt with the unseen graphemes by using metric learning. They used Arcface (Deng et al. 2019) to determine if an input test sample is present or absent in the train dataset. If the grapheme is present, a single EfficientNet model is used that detects the grapheme components in a multi-task setting. Otherwise, a different EfficientNet models are used to recognize each grapheme component.

5.3 Submission Insights

For exploratory analysis on the competition submissions, we take the top 20 teams from both the private and public test set leaderboards and categorize their submissions according to quantile intervals of their private set scores as *Tier 1* ($> .976$), *Tier 2* ($> .933, < .976$), *Tier 3* ($> .925, < .933$) and *Tier 4* ($> .88, < .925$). It is seen that the *Tier 4* submissions have low discrepancy between public and private test set metrics; suggesting these to be high bias - low variance estimators. The *Tier 3* submissions were the total opposite and had high discrepancy on average, indicating fine-tuning of the model on the public test set. This discrepancy increases as we go to *Tier 2* submissions but then decreases for *Tier 1* submissions. In fact if we observe the progression of the *Tier 2* teams, many of them were once near the top of the private leaderboard but later fine-tuned for the public test set. Contrary to intuition, error rate doesn't significantly vary depending on the frequency of the unique grapheme in the training set, within each of these quantile groups. However, the error rate is higher by 1.31% on average for unseen graphemes, with *Tier 1* error rate at $4.4(\pm 0.07)\%$.

Considering the size of the challenge test set, possible reasons behind test set error could be label noise, class imbalance or general challenges surrounding the task. We start by inspecting the samples that were misclassified by all the *Tier 1* submissions and find that only 34.8% had label noise. Significant error can be seen due to the misclassification of consonant diacritic classes which are binary combinations of {'◌্য','্র' or 'র্'}, with high false positives for the individual constituents. This can be attributed to the class imbalance in the dataset since combinations are less frequent that their primitives; separately recognizing the primitives in a multi-label manner could be a possible way to reduce such error. The vowel diacritic component has the highest macro-averaged recall, proving to be the easiest among the three tasks.

The false negatives of different grapheme roots give us significant insights on the challenges present in Bengali orthography. A pair of grapheme roots can have

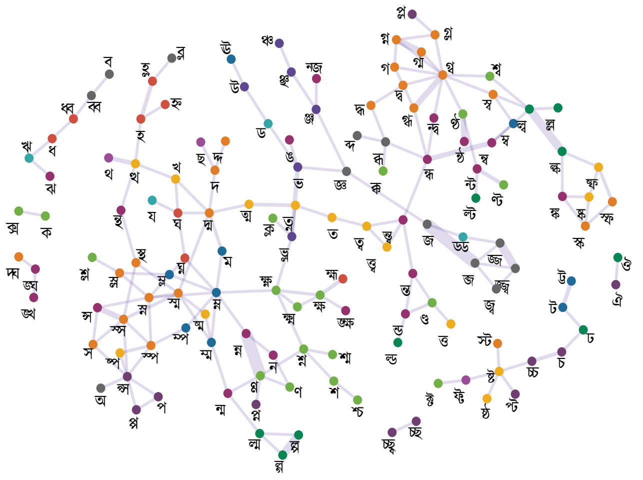


Figure 6: Similarity between handwritten grapheme roots based on *Tier 1* confusion. Nodes are color coded according to the first character in each root. Edges correspond to sum of false negative rates between nodes, higher edge width corresponds to higher similarity between handwritten grapheme roots.

high similarity due to common characters or even similarity between glyphs of constituents. Probing the *Tier 1* false negatives, we find that 56.5% of the error is between roots that share at least one character. Misclassification between consonant conjuncts with the same first and second characters accounts for 28.8% and 21.5% of the error. Confusion between roots by *Tier 1* submissions highly correlate with similarity between glyphs and is visualized in Fig. 6. Edges correspond to the sum of false negative rates between nodes and is pruned if the sum is below .5%. Separate networks are formed by groups that are similar to each other but dissimilar with other. Class imbalance also plays an interesting role in such cases; misclassification of roots with high similarity between their handwritten glyphs can also be biased towards one class due to higher frequency, eg. roots with 'ণ' are more frequently misclassified as roots with 'ন' because of 'ন' being more frequent.

6 Discussions and Future work

In the competition, we have formulated the grapheme recognition challenge as a multi-label classification task but it is only one way of defining the grapheme recognition problem. It can also be posed as firstly, a sequence mapping task- where each character in the Unicode string is mapped to its corresponding glyph- and secondly a multi-label sequence mixture problem where the grapheme root is a sequence of characters while diacritics are separate labels with orthogonal classes. Since there are many graphemes that are possible but never used in practice, the dataset can also be used to generate new graphemes (as demonstrated in Section 5.2) that are not in the dataset or less used in practice. One aspect not explored at all here is the possibility of generating consonant conjuncts not present in the dataset. Generating realistic consonant conjuncts could lead to better performances, especially on allographs.

Alongside benchmarking multi-task algorithms, this dataset can be used for evaluating the performance of generative models. The number of possible graphemes are extremely large but fixed to a finite number and governed by specific linguistic rules. So, the latent space of a well trained model should be able to capture a range of meaningful grapheme combinations. This is unlike what we expect from some more high dimensional data like CelebA (Liu et al. 2015) as there are constraints on the shape of human faces. Additionally, the grapheme dataset is relatively free from background clutter often found in CelebA dataset.

7 Conclusion

In this paper, we outlined the challenges of recognizing Bengali handwritten text and explained why a character based labeling scheme- that has been widely successful for English characters- does not transfer well to Bengali. To rectify this, we propose a novel labeling scheme based on graphemes and present a dataset based on this scheme. Crowd sourced benchmarking on Kaggle shows that algorithms trained on this dataset can generalize on unseen graphemes. This proves that it is possible to summarize the entire cohort of graphemes through some representative samples. This grapheme labeling scheme could be used as a stepping stone to solve OCR related tasks in not only Bengali but also other related languages in the alpha-syllabary family.

Acknowledgements

We would like to thank Kaggle for their generous support through the Kaggle platform. We would like to thank the late Dr. Ali Shihab Sabbir for providing invaluable help and guidance to Bengali.AI since its inception. We are also grateful to our volunteers who participated and helped organize collection of data for our dataset. Full list of contributions available at https://rb.gy/qd3ur2.

References

Acharya, S.; Pant, A. K.; and Gyawali, P. K. 2015. Deep learning based large scale handwritten Devanagari character recognition. In *Proc. 9th Int. Conf. SKIMA)*, 1–6.

Alam, S.; Reasat, T.; Doha, R. M.; and Humayun, A. I. 2018. NumtaDB - Assembled Bengali Handwritten Digits. *arXiv preprint arXiv:1806.02452* .

AlKhateeb, J. H. 2015. A Database for Arabic Handwritten Character Recognition. *Procedia Computer Science* 65: 556 – 561.

Berthelot, D.; Carlini, N.; Goodfellow, I.; Papernot, N.; Oliver, A.; and Raffel, C. 2019. MixMatch: A Holistic Approach to Semi-Supervised Learning. In *Proc. NeurIPS, 2019.*

Biswas, M.; Islam, R.; Shom, G. K.; Shopon, M.; Mohammed, N.; Momen, S.; and Abedin, M. A. 2017. BanglaLekha-Isolated: A Comprehensive Bangla Handwritten Character Dataset. *arXiv preprint arXiv:1703.10661* .

Bright, W. 1999. A Matter of Typology: Alphasyllabaries and Abugidas. *Written Language & Literacy* 2(1): 45–65.

Deng, J.; Guo, J.; Xue, N.; and Zafeiriou, S. 2019. ArcFace: Additive Angular Margin Loss for Deep Face Recognition. In *Proc. 2019 IEEE/CVF Conf. CVPR.*

DeVries, T.; and Taylor, G. W. 2017. Improved regularization of convolutional neural networks with cutout. *arXiv preprint arXiv:1708.04552* .

Dutta, K.; Krishnan, P.; Mathew, M.; and Jawahar, C. V. 2018. Offline Handwriting Recognition on Devanagari Using a New Benchmark Dataset. In *Proc. 13th IAPR Int. Workshop DAS*, 25–30.

Farrahi Moghaddam, R.; Cheriet, M.; Adankon, M. M.; Filonenko, K.; and Wisnovsky, R. 2010. IBN SINA: A Database for Research on Processing and Understanding of Arabic Manuscripts Images. In *Proc. 9th IAPR Int. Workshop DAS*, 11–18.

Fedorova, L. 2013. The Development of Graphic Representation in Abugida Writing: The Akshara's Grammar. *Lingua Posnaniensis* 55(2): 49–66.

Harris, E.; Marcu, A.; Painter, M.; Niranjan, M.; Prügel-Bennett, A.; and Hare, J. 2020. FMix: Enhancing Mixed Sample Data Augmentation. *arXiv e-prints* arXiv:2002.12047.

Hu, J.; Shen, L.; and Sun, G. 2018. Squeeze-and-Excitation Networks. In *Proc. IEEE/CVF Conf. CVPR, 2018*, 7132–7141. ISSN 2575-7075.

Kjartansson, O.; Sarin, S.; Pipatsrisawat, K.; Jansche, M.; and Ha, L. 2018. Crowd-Sourced Speech Corpora for Javanese, Sundanese, Sinhala, Nepali, and Bangladeshi Bengali. In *Proc. 6th Intl. Workshop SLTU*, 52–55.

Liu, Z.; Luo, P.; Wang, X.; and Tang, X. 2015. Deep Learning Face Attributes in the Wild. In *Proc. ICCV.*

Obaidullah, S. M.; Halder, C.; Das, N.; and Roy, K. 2016. A New Dataset of Word-Level Offline Handwritten Numeral Images from Four Official Indic Scripts and Its Benchmarking Using Image Transform Fusion. *Int. J. Intell. Eng. Inform.* 4(1): 1–20.

Rabby, A. S. A.; Haque, S.; Islam, M. S.; Abujar, S.; and Hossain, S. A. 2019. Ekush: A Multipurpose and Multitype Comprehensive Database for Online Off-Line Bangla Handwritten Characters. In *RTIP2R*, 149–158.

Sarkar, R.; Das, N.; Basu, S.; Kundu, M.; Nasipuri, M.; and Basu, D. K. 2012. CMATERdb1: a database of unconstrained handwritten Bangla and Bangla–English mixed script document image. *IJDAR* 15(1): 71–83.

Tan, M.; and Le, Q. 2019. EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. In *PMLR*, volume 97, 6105–6114.

Yun, S.; Han, D.; Chun, S.; Oh, S. J.; Yoo, Y.; and Choe, J. 2019. CutMix: Regularization Strategy to Train Strong Classifiers With Localizable Features. In *Proc. ICCV, 2019*, 6022–6031.

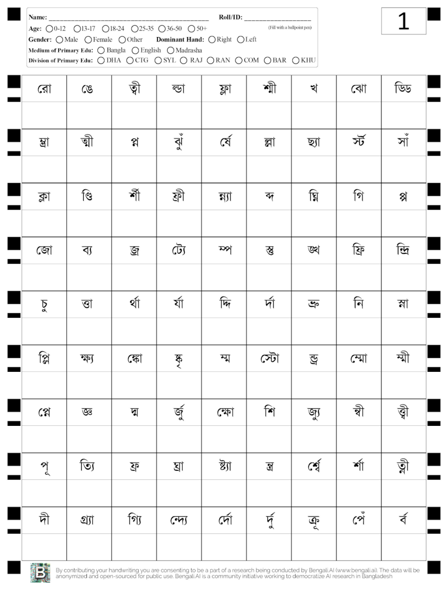
Zhang, H.; Cisse, M.; Dauphin, Y. N.; and Lopez-Paz, D. 2017. Mixup: Beyond empirical risk minimization. *arXiv preprint arXiv:1710.09412* .

Zhu, J.; Park, T.; Isola, P.; and Efros, A. A. 2017. Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks. In *Proc. ICCV, 2017*, 2242–2251.

Appendix

A Grapheme Collection Form

Handwritten Graphemes were collected from 16 different template forms designed for efficient extraction by scanning. Forms also had additional information that include chirality, age group, gender, medium of instruction and location of primary school to allow for further study into handwriting. Names and IDs were collected to keep into account multiple forms submitted by the same person; but were later de-identified. A sample form is showed in Fig. 7



Name: ______________________ Roll/ID: __________

Age: ◯0-12 ◯13-17 ◯18-24 ◯25-35 ◯36-50 ◯50+ (Fill with a ballpoint pen)

Gender: ◯Male ◯Female ◯Other Dominant Hand: ◯Right ◯Left

Medium of Primary Edu: ◯Bangla ◯English ◯Madrasha

Division of Primary Edu: ◯DHA ◯CTG ◯SYL ◯RAJ ◯RAN ◯COM ◯BAR ◯KHU

1

রো	ঙে	ত্বী	ল্ডা	ফ্লা	শ্মী	খ	ঝো	ডিড
ম্রা	ত্মী	প্ন	ঝুঁ	র্ষে	ল্লা	ছ্যা	র্স্ট	সাঁ
ক্লা	ঙি	র্শী	ফ্রী	ন্ন্যা	ব্দ	ঘ্নি	গি	প্প
জো	ব্য	জ্র	ট্যৈ	স্প	স্ত	ঙ্খ	ফ্রি	ন্দ্রি
চু	ত্তা	র্থা	র্যা	দ্দি	র্দা	ভ্রু	নি	স্না
প্লি	ক্ষ্য	ঙ্কো	ষ্কৃ	ম্ম	স্টো	ড্র	স্মো	স্মী
প্নে	জ্ঞ	দ্ম	র্জু	ক্ষো	শি	জ্যু	ন্বী	ত্ত্বী
পৃ	ত্যি	ফ্র	ঘ্রা	ষ্ট্যা	ন্ত্র	র্শ্বে	র্শা	ত্নী
দী	গ্র্যা	গ্যি	ন্দ্যে	র্দো	র্দু	ক্রূ	পেঁ	র্ব

By contributing your handwriting you are consenting to be a part of a research being conducted by Bengali.AI (www.bengali.ai). The data will be anonymized and open-sourced for public use. Bengali.AI is a community initiative working to democratize AI research in Bangladesh

Figure 7: Sample of OCR form for extracting handwritten graphemes

B Dataset collection & standardization

The data was obtained from volunteers in schools, colleges and universities across Bangladesh. A standardized form A with alignment markers were printed and distributed. A total of 2896 volunteers participated in the project. Each subject could be uniquely identified through their institutional identification number submitted through the forms. A random subject identifier was generated for each individual and the identifying information was removed. A summary of the dataset compilation protocol is detailed below:

Step 1: Collection The candidate data for the dataset was collected using forms where contributors filled up boxes with handwritten graphemes as prompted in boxes. There were 16 different form templates spanning the 1295 different graphemes to be collected. The templates were automatically generated using Adobe Photoshop scripts. Each template had a unique set of graphemes from the others. Since the 16 different templates were not dispersed uniformly every time data was collected, minor sampling bias was introduced during collection.

Step 2: Pruning and Scanning The forms were scanned and analysed carefully to remove invalid submissions and reduce sampling bias. In this step additional errors were introduced due to misalignment during scanning. Unfilled or improperly filled samples were still retained. All the forms were scanned using the same device at 300 dpi.

Step 3: Extraction An OCR algorithm was used to automatically detect the template ID. The template identifier asserted which ground truth graphemes where present in which boxes of the form. In this step, OCR extraction errors introduced label noise. The scanned forms were registered with digital templates to extract handwritten data, which sometimes introduced alignment errors or errors while extracting metadata. Unfilled boxes were removed automatically in this step.

Step 4: Preliminary Label Verification The extracted graphemes were compiled into batches and sent to 22 native Bengali volunteers who analysed each image and matched them to their corresponding ground truth annotation. In this step OCR errors and label noise was minimised. However additional error was introduced in the form of conformity bias, linguistic bias (i.e. allograph not recognized), grapheme bias (i.e. particular grapheme has significantly lesser number of samples) and annotator subjectivity. Samples selected as erroneous by each annotator was stored for further inspection instead of being discarded.

Step 5: Label Verification Each batch from the previous step, was sent to one of two curators who validated erroneous samples submitted by annotators and re-checked unique graphemes which had a higher frequency of mislabeled samples.

Step 6: Subjectivity Normalization A fixed guideline is decided upon by all curators that specifies how much and the nature of deformity a sample can contain. Based on this, subjectivity errors were minimized for unique graphemes with high frequency mislabeled samples.

C Dataset Summary

A breakdown of the composition of the dataset is given in Table 3. Note that the absence of a diacritic which is

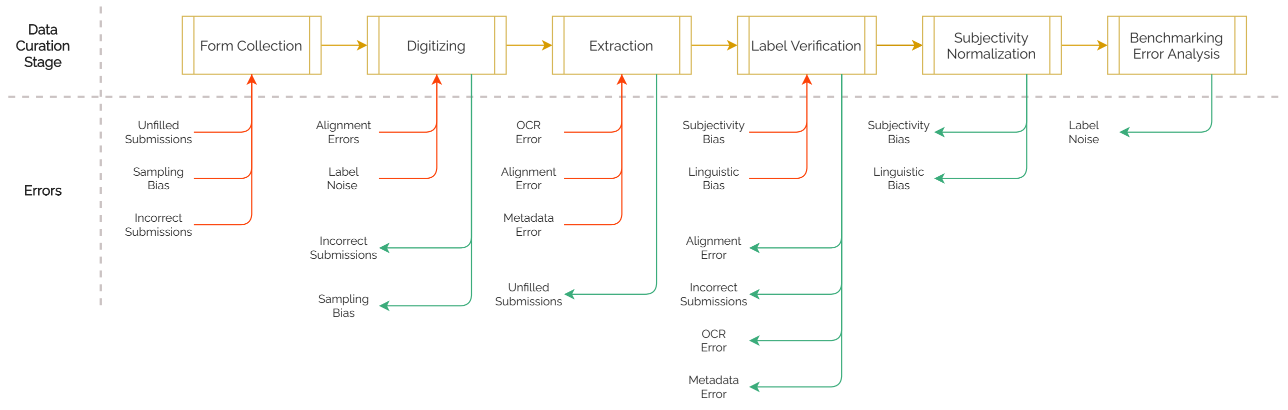


Figure 8: Overview of dataset creation process. Green arrows refer to the bias/errors removed in each step and red refers to the ones inevitably introduced.

Table 1: Frequently discarded graphemes during label verification phases of dataset curation

Root Category	Top 5 Graphemes				
Consonants	গুঁ	র্গু	গু	শ্যু	ঘৃ
2nd order Conjuncts	ষ্ট্যা	ঙ্কৃ	ষ্পা	ঙ্ক	ষ্ক্রী
3rd order Conjuncts	ঙ্ক্তি	ক্ষ্ণ	ক্ষ্ণৌ	ঙ্ক্ষা	ন্দ্বি

labeled as the null diacritic '0' is not considered when counting the total samples as the glyph for the diacritic is not present in such samples. In the table a breakdown of the roots into vowels, consonants and conjuncts is also shown to further solidify the imbalance in class that occurs.

D Contribution Error and Subjectivity

The original data went through a rigorous curation process; approximately 12817 samples were discarded due to either label noise or corrupted submissions. Samples that would be illegible to human annotators without prior knowledge of the ground truth were discarded from the dataset. Although this was done to make sure the data is clean, it should be mentioned that a concrete definition of which samples should be considered legible does not exist. In fact some would consider a written sample perfectly legible while others would consider the same as absolutely unclear. If we look at the error data, among the top 100 unique graphemes that had the most erroneous contributions, 83 had consonant conjuncts as the grapheme root. Six out of the nine 3$^{\text{rd}}$ order consonant conjuncts in the dataset, were among the most erroneous graphemes. This matches the intuition that more complex grapheme glyphs are harder to discern as writers are more likely to make mistakes in typography when writing glyphs with more intricate patterns. The most common errors in writing graphemes categorized by the number of simple consonants in the root are given in Table 1.

E Label-Class Overview in Dataset

All classes for each of the three labels have been listed in their utf-8 form in Table 2. Note that all the diacritics are shown in a grapheme with root ব as an example. Their glyphs will, however, appear unchanged with any other root.

F Consonant Conjuncts vs Diacritics

One question that arises while splitting the constituents of a grapheme into the three bins of our labeling scheme (see Section 4.2) is the ambiguity between consonant conjuncts and consonant diacritics. While conjuncts are formed by adding multiple consonants together, consonant diacritics also add consonants with other consonants but as demarcations that are completely different from the original glyph of the consonant. For example, the consonant diacritic '্য' is completely different from its original form 'য'. Whenever it is added to a consonant root, the root retains its original glyph. This is not always the case for consonant conjuncts, where the consonants being added to might change its form significantly. In Bengali grammar, consonant diacritics are called *Fola* and defined separately from consonant conjuncts as *Jukto Borno*. The consonants that have diacritic forms do not construct conjuncts, eg. 'য' and 'র' are not present as a second order conjunct constituent in Fig. 5.

G Training Set Metadata

The metadata collected through forms are compiled together for further studies on dependency of handwriting with each of the meta domains. Only the training set metadata is made public; the test set metadata will be made available upon request for benchmarking handwriting dependency with the metadata. The training set contains handwriting from 1448 individuals, each individual contributing 138.8 graphemes on average; 1037 of the contributors identified as male, 383 as female, 4 as non-binary and 24 declined to identify. The medium of

Table 2: Table of all labels and classes present in the dataset. Diacritics are written in their graphemic forms with grapheme root 'ব'. Phonetic transliterations in IPA standards are provided in brackets (·).

Label	Class
Grapheme roots (168)	VOWEL ROOTS অ (a), আ (ā), ই (i), ঈ (ī), উ (u), ঊ (ū), ঋ (r), এ (ē), ঐ (ai), ও (ō), ঔ (au) CONSONANT ROOTS ক (ka), খ (kha), গ (ga), ঘ (gha), ঙ (ṅa), চ (ca), ছ (cha), জ (ja), ঝ (jha), ঞ (ña), ট (ṭa), ঠ (ṭha), ড (ḍa), ঢ (ḍha), ণ (ṇa), ত (ta), থ (tha), দ (da), ধ (dha), ন (na), প (pa), ফ (pha), ব (ba), ভ (bha), ম (ma), য (ya), র (ra), ল (la), শ (śa), ষ (ṣa), স (sa), হ (ha), ড় (ṛa), ঢ় (ṛha), য় (ẏa), ◌ং (ṁ), ◌ঃ (ḥ), ৎ (t̲) CONJUNCT ROOTS ক্ক (kka), ক্ট (kṭa), ক্ত (kta), ক্ল (kla), ক্ষ (kṣa), ক্ষ্ণ (kṣṇa), ক্ষ্ম (kṣma), ক্স (ksa), গ্ধ (gdha), গ্ন (gna), গ্ব (gba), গ্ম (gma), গ্ল (gla), ঘ্ন (ghna), ঙ্ক (ṅka), ঙ্ক্ত (ṅkta), ঙ্ক্ষ (ṅkṣa), ঙ্খ (ṅkha), ঙ্গ (ṅga), ঙ্ঘ (ṅgha), চ্চ (cca), চ্ছ (ccha), চ্ছ্ব (cchba), জ্জ (jja), জ্জ্ব (jjba), জ্ঞ (jña), জ্ব (jba), ঞ্চ (ñca), ঞ্ছ (ñcha), ঞ্জ (ñja), ট্ট (ṭṭa), ড্ড (ḍḍa), ণ্ট (ṇṭa), ণ্ঠ (ṇṭha), ণ্ড (ṇḍa), ণ্ণ (ṇṇa), ত্ত (tta), ত্ত্ব (ttba), ত্থ (t'tha), ত্ন (tna), ত্ব (tba), ত্ম (tma), দ্ঘ (dgha), দ্দ (dda), দ্ধ (d'dha), দ্ব (dba), দ্ভ (dbha), দ্ম (dma), ধ্ব (dhba), ন্জ (nja), ন্ট (nṭa), ন্ঠ (nṭha), ন্ড (nḍa), ন্ত (nta), ন্ত্ব (ntba), ন্থ (ntha), ন্দ (nda), ন্দ্ব (ndba), ন্ধ (ndha), ন্ন (nna), ন্ব (nba), ন্ম (nma), ন্স (nsa), প্ট (pṭa), প্ত (pta), প্ন (pna), প্প (ppa), প্ল (pla), প্স (psa), ফ্ট (phṭa), ফ্ফ (phpha), ফ্ল (phla), ব্জ (bja), ব্দ (bda), ব্ধ (bdha), ব্ব (bba), ব্ল (bla), ভ্ল (bhla), ম্ন (mna), ম্প (mpa), ম্ব (mba), ম্ভ (mbha), ম্ম (m'ma), ম্ল (mla), ল্ক (lka), ল্গ (lga), ল্ট (lṭa), ল্ড (lḍa), ল্প (lpa), ল্ব (lba), ল্ম (lma), ল্ল (lla), শ্চ (śca), শ্ন (śna), শ্ব (śba), শ্ম (śma), শ্ল (śla), ষ্ক (ṣka), ষ্ট (ṣṭa), ষ্ঠ (ṣṭha), ষ্ণ (ṣṇa), ষ্প (ṣpa), ষ্ফ (ṣpha), ষ্ম (ṣma), স্ক (ska), স্ট (sṭa), স্ত (sta), স্থ (stha), স্ন (sna), স্প (spa), স্ফ (spha), স্ব (sba), স্ম (sma), স্ল (sla), স্স (s'sa), হ্ন (hna), হ্ব (hba), হ্ম (hma), হ্ল (hla)
Vowel Diacritics (11)	Null, বা (bā), বি (bi), বী (bī), বু (bu), বূ (bū), বে (bē), বৈ (bai), বো (bō), বৌ (bau)
Consonant Diacritics (8)	Null, ব্য (bya), ব্র (bra), র্ব (rba), র্ব্য (rbya), ব্র্য (brya), র্ব্র (rbra), বঁ (b̆)

Table 3: Number of samples present in each subset of the dataset. Null diacritics are ignored.

Labels	Sub-labels	Classes	Samples	Training Set	Public Test Set	Private Test Set
Roots	Vowel Roots	11	5315	2672	1270	1398
	Consonant Roots	38	215001	107103	52185	57787
	Conjunct Roots	119	184050	91065	45206	53196
	Total	168	404366	200840	98661	112381
Diacritics	Vowel Diacritics	10	320896	159332	78503	89891
	Consonant Diacritics	7	152010	75562	37301	44649

instruction during primary education for 1196 contributors was Bengali, for 214 English and for 12 Madrasha (Bengali and Arabic); 33 are left-handed while 1192 are right handed. Of all the contributors, 93 fall in the age group between $0-12$, 245 in $13-17$, 1057 in $18-24$, 22 in $25-35$ and 2 in ages between $36-50$.

H Rank Progression in Competition

To benchmark the dataset extensively, a Kaggle competition was organized based on this dataset. This resulted in 31,002 submissions from 2,059 teams consisting of 2,623 competitors. Analyzing the submissions allowed us to further discover important statistics on this dataset. Since the competition was held with half the test set hidden, it is important to know when the model

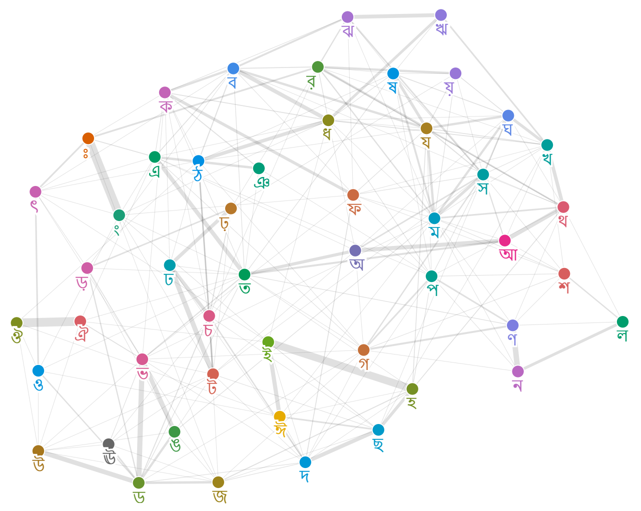


Figure 9: Similarity between handwritten non-conjunct roots based on Tier 1 confusion scores. Edges correspond to sum of false negative rates between nodes, higher edge width corresponds to higher similarity. Only roots with an error rate more than 15% are shown in the figure.

is over-fitting and find ways to generalize for unseen data. Without proper tuning, large models will tend to over-fit on the public test set and perform poorly on the private one. This is shown in Fig. 10. Five teams' progression has been highlighted (randomly) and the others grayed out. Notice how the teams marked 🟥 and 🟨 were able to decrease their score discrepancy and jump up in rank. The teams marked 🟧, 🟩 and 🟦, scored high in the private test set at some point but over-fit thereafter falling in rank. A major reason for many of the teams over-fitting to the public set is that the test set distribution is somewhat different from the training distribution. The problem is compounded by the presence of grapheme combinations in the test set that are not present in the train set. These account for about 3.5% of test samples. So it is crucial that steps be taken to check if models trained on the dataset use augmentation and generative techniques to match the distribution of the test set. The issue of generalization can be further checked by seeing how a model performs on samples that are comparatively less frequent in the training set. We took all submissions that were reasonably good (top 75% among all submissions corresponding to a private score of 0.88) and classified them further into four classes - *Tier 1* (Top 25%, score > 0.976), *Tier 2* (Between 25% and 50%, $0.933 <$ score < 0.976), *Tier 3* ((Between 50% and 75%, $0.925 <$ score < 0.933) and *Tier 4* (Bottom 25%, $0.88 <$ score < 0.925). We mapped their performance against their public-private score discrepancy defined as the difference, Δ between their public and private scores as shown in Table 4. The discrepancy levels were categorized according to their quantile intervals and the number of submissions belonging to that interval are shown in the table. Notice how the *Tier 4* submissions category have low discrepancy. These submissions were high bias - low variance. The *Tier 3* submissions category were the total opposite and had mostly high discrepancy. These submissions were over-fitting to the training data. However, notice the transition that occurs between *Tier 2* and the *Tier 1* models in terms of the change in the number of low and high discrepancy submissions. The *Tier 2* submissions were from models that were over optimized for the public test set which degraded their performance on the private set. Another important aspect to see is how the different models were performing with regard to the number of samples present in the training set. We categorized the frequency of each unique graphemes in the training set, f according to quartile division. The the specific intervals are $f > 165$ (the top 25% most frequent graphemes in the training set) $157 < f \leq 165$,$143 < f \leq 157$, $0 < f \leq 143$(the bottom 25%). Additionally, the graphemes not present in training set were correspond to $f = 0$. The performance of each Tier is tabulated in Table 5. One thing to notice here is that the error rate of graphemes is significantly higher for the *Tier 4* class (The error rate here is the percentage of graphemes the submission predicted incorrectly and is not the same as the competition score). Additionally, better submissions perform better in general. However, the error rate on the unseen set is still higher than the other categories

Table 4: Public-Private score discrepancy in the submissions by Top 20 teams

Performance Class	Public-Private Discrepancy,Δ	Number of Submissions
Tier 4	$\Delta \leq 0.04$	392
	$0.4 < \Delta < 0.06$	211
	$\Delta \geq 0.06$	116
Tier 3	$\Delta \leq 0.04$	100
	$0.04 < \Delta < 0.06$	158
	$\Delta \geq 0.06$	461
Tier 2	$\Delta \leq 0.04$	27
	$0.04 < \Delta < 0.06$	191
	$\Delta \geq 0.06$	500
Tier 1	$\Delta \leq 0.04$	201
	$0.04 < \Delta < 0.06$	159
	$\Delta \geq 0.06$	361

I Confusion between consonant and vowel roots of Tier 1 submissions

It has been suggested in 4.4 that class imbalance could cause models to focus on features of roots and diacritics that are more frequent in the dataset. Due to nature of Bengali orthography, many glyphs share features that are very similar. This causes model to confuse an in-

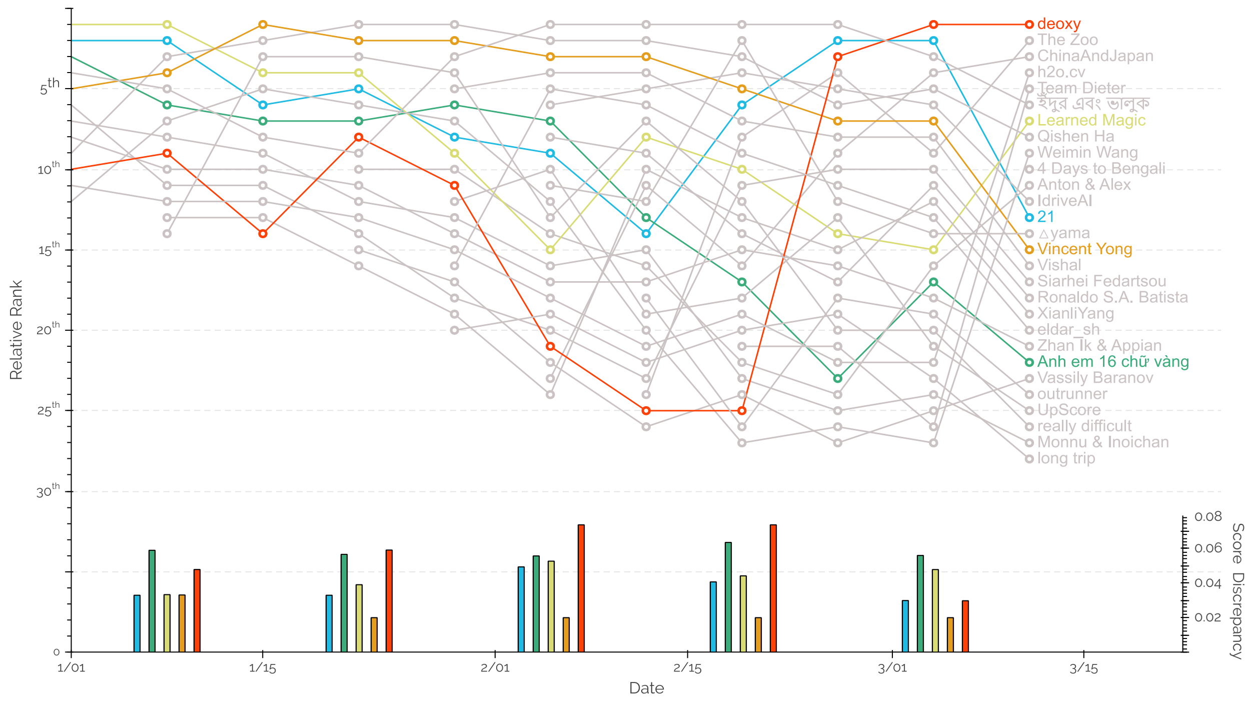


Figure 10: Figure showing how the relative rank of selected teams changed during the competition. Some teams have been highlighted and their corresponding public-private score difference represented by the bar diagrams.

frequent grapheme in the dataset to be misclassified as a more frequent one. It is therefore essential to understand which features of a glyph the models are putting importance on. This may be approximated by looking at how much each consonant root has been misclassified in the form of a confusion network graph shown in Fig. 9. We can notice here that many of the misclassified roots are expected. For example, হ and ই are miscalssified more frequently by the *Tier 1* models and this can be attributed to the similarity of their glyphs. However, there are other consonant roots like ও and ঐ which do not share strong similarity but are still misclassified frequently. This suggests that the models focused more on the tail that is seen on these characters instead of their primary structure.

Table 5: Generalization performance with respect to different grapheme training frequencies

Performance Tiers	Training frequency, f	Test Error Rate(%)
Tier 4	$f > 165$	28.42
	$157 < f \leq 165$	28.34
	$143 < f \leq 157$	28.42
	$0 < f \leq 143$	28.42
	$f = 0$	29.68
Tier 3	$f > 165$	4.47
	$157 < f \leq 165$	4.36
	$143 < f \leq 157$	4.48
	$0 < f \leq 143$	4.48
	$f = 0$	6.02
Tier 2	$f > 165$	3.86
	$157 < f \leq 165$	3.77
	$143 < f \leq 157$	3.90
	$0 < f \leq 143$	3.87
	$f = 0$	5.27
Tier 1	$f > 165$	3.37
	$157 < f \leq 165$	3.29
	$143 < f \leq 157$	3.41
	$0 < f \leq 143$	3.41
	$f = 0$	4.44