

**DEVELOPMENT OF INTELLIGENT
CHARACTER RECOGNITION MODEL
INSPIRED BY COGNITIVE EXPERIMENTS**

Chetan Sudarshan Ralekar



DEPARTMENT OF ELECTRICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY DELHI

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INSPIRED BY COGNITIVE EXPERIMENTS**

by

Chetan Sudarshan Ralekar

DEPARTMENT OF ELECTRICAL ENGINEERING

Submitted

in fulfillment of the requirements of the degree of Doctor of Philosophy

to the



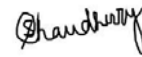
INDIAN INSTITUTE OF TECHNOLOGY DELHI

NOVEMBER 2021

Dedicated to my family...

Certificate

This is to certify that the thesis titled “**Development of Intelligent Character Recognition Model Inspired by Cognitive Experiments**” being submitted by **Chetan Sudarshan Ralekar** to the **Department of Electrical Engineering**, Indian Institute of Technology Delhi, for the award of **Doctor of Philosophy** is a record of bonafide research work carried out by her under my guidance and supervision. In my opinion, the thesis has reached the standards fulfilling the requirements of the regulations relating to the degree. The work presented in this thesis has not been submitted elsewhere, either in part or full, for the award of any other degree or diploma.



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Abstract

Character recognition has been one of the most contemporary and challenging areas of research for decades. The past research on developing character recognition models using image processing and computer vision-based techniques shows that ‘character recognition’ is assumed to be a pure machine vision optimization problem. However, humans are still better at recognizing many characters especially distorted, ornamental or calligraphic characters as compared to the highly sophisticated recognition models. Although understanding the mechanism of character recognition by humans may give us some cues leading to better recognition abilities, the appropriate methodological approach of using these cues has not been much explored for developing character recognition models. Therefore, in this thesis, we propose to perform some cognitive experiments with humans to obtain some cues which will be used to develop intelligent character recognition models.

We start the investigation by understanding the reading behavior followed by distorted and ornamental character recognition through the analysis of the eye movement data. The experimental results show that humans direct their gaze to specific regions contributing to the character identity and recognize the characters using those key character regions. To highlight the character regions influencing the model’s decision, we have proposed a ‘modified Grad-CAM visualization technique’, which is one of the contributions in the domain of explainable AI. Qualitative comparison between visualization maps and eye-fixation maps reveals that the deep learning model considered similar regions in character, which humans have fixated on, in the case of correctly classified characters. On the other hand, when the focused regions are different for humans and deep nets, the characters are typically misclassified by the latter. Both

visualization maps and fixation maps are used to develop a visual explanation guided attention model (VEGAM). Furthermore, this thesis presents distinct attention models such as the deeply supervised and collaborative attention models that signify the importance of foveal and parafoveal vision in recognition. The experimental design, data analysis, and results presented in this thesis demonstrate the effectiveness of the proposed approaches.

Owing to a sophisticated vision system, vast visual experience, rich cognitive and perceptual processes, humans have a distinct edge over machines in the recognition task. The behavioral experiments using Bubble and proposed RISE (Random image structure evolution) stimuli emphasize the presence of some higher-level cognitive processes aiding successful recognition. In this era of AI, researchers are striving hard to build systems that can match human intelligence. One way to bridge the gap between machine and human intelligence is to design the artificial systems using cues derived from their natural counterpart, such as through cognitive experiments on human participants. This thesis, henceforth, motivates the need for substantial efforts in exploring various aspects of the cognitive processes to develop the next generation collaborative models for mimicking the human intelligence in AI-driven Engineering systems.

सार

करैक्टर रिकग्निशन (अक्षर पहचान) दशकों से सबसे समकालीन और चुनौतीपूर्ण अनुसंधान के क्षेत्रों में से एक रहा है। इमेज प्रोसेसिंग (छवि प्रसंस्करण) और कंप्यूटर दृष्टि-आधारित तकनीकों का उपयोग करके करैक्टर रिकग्निशन मॉडल विकसित करने के पिछले कई शोधों से पता चलता है कि 'करैक्टर रिकग्निशन' को सिर्फ मशीन दृष्टि अनुकूलन समस्या माना जा रहा है। हालांकि, अत्यधिक परिष्कृत मान्यता मॉडल की तुलना में मनुष्य अभी भी कई करैक्टर्स को; विशेष रूप से, विकृत, सजावटी या सुलेख अक्षरों को पहचानने में बेहतर हैं। यद्यपि मनुष्यों द्वारा करैक्टर रिकग्निशन के तंत्र को समझने से हमें कुछ संकेत मिल सकते हैं, जिससे बेहतर पहचान (रिकग्निशन) क्षमता हो सकती है। किन्तु करैक्टर रिकग्निशन मॉडल विकसित करने के लिए इन संकेतों का उपयोग करने के उपयुक्त पद्धतिगत दृष्टिकोण का अधिक पता नहीं लगाया गया है। इसलिए, इस थीसिस में, हम कुछ संकेत प्राप्त करने के लिए मनुष्यों के साथ कुछ संज्ञानात्मक प्रयोग करने का प्रस्ताव करते हैं, जिनका उपयोग बुद्धिमान करैक्टर रिकग्निशन मॉडल को विकसित करने के लिए किया जाएगा।

हम आंखों की गति के विश्लेषण के माध्यम से पढ़ने के व्यवहार को समझकर विकृत और सजावटी करैक्टर रिकग्निशन की जांच शुरू करते हैं। प्रायोगिक परिणामों से पता चलता है कि मनुष्य करैक्टर रिकग्निशन में योगदान देने वाले विशिष्ट क्षेत्रों (रीजन) की ओर अपनी आंखें टिकाता है और उन प्रमुख क्षेत्रों का उपयोग करके करैक्टर (अक्षर) को पहचानते हैं। मॉडल के निर्णय को प्रभावित करने वाले करैक्टर क्षेत्रों को उजागर करने के लिए, हमने एक 'संशोधित ब्रैड-कॉम' विजुअलाइजेशन तकनीक का प्रस्ताव दिया है, जो एक्सप्लेनेबल एआई के क्षेत्र के योगदानों में से एक है। विजुअलाइजेशन मैप्स और आई-फिक्सेशन मैप्स के बीच गुणात्मक तुलना से पता चलता है कि डीप लर्निंग मॉडल ने करैक्टर में समान क्षेत्रों को माना, जिसे मनुष्यों ने ठीक से वर्गीकृत वर्णों के मामले में तय किया है। दूसरी ओर, जब मनुष्यों और डीप लर्निंग मॉडल के केंद्रित क्षेत्र भिन्न होते थे, तो करैक्टर को आम तौर पर मॉडल द्वारा गलत वर्गीकृत किया गया। विजुअल एक्सप्लेनेशन गाइडेड अटेंशन मॉडल (वीईजीएएम) विकसित करने के लिए विजुअलाइजेशन मैप्स और फिक्सेशन मैप्स दोनों का उपयोग किया जाता है। इसके अलावा, यह थीसिस अलग-अलग अटेंशन मॉडल प्रस्तुत करता है, जैसे कि डीपली सुपरवाइज़ और कोल्लेबोरेटिव मॉडल्स, जो मान्यता में फोवियल और पैराफोवेल दृष्टि के महत्व को दर्शाते हैं। इस थीसिस में प्रस्तुत प्रयोगात्मक डिजाइन, डेटा विश्लेषण और परिणाम प्रस्तावित दृष्टिकोणों की प्रभावशीलता को प्रदर्शित करते हैं।

एक परिष्कृत दृष्टि प्रणाली, विशाल दृश्य अनुभव, समृद्ध संज्ञानात्मक और अवधारणात्मक प्रक्रियाओं के कारण, मनुष्यों की 'पहचान कार्य' में मशीनों पर एक अलग बढ़त है। बबल और प्रस्तावित RISE (रैंडम इमेज स्ट्रक्चर इवोल्यूशन) सिस्टम्युलि का उपयोग करने वाले प्रयोग कुछ उच्च-स्तरीय संज्ञानात्मक प्रक्रियाओं की उपस्थिति पर जोर देते हैं; जो सफल अक्षर पहचान कार्य की सहायता करते हैं। एआई के इस युग में, शोधकर्ता ऐसे सिस्टम बनाने के लिए कड़ी मेहनत कर रहे हैं जो मानव बुद्धि से मेल खा सकें। मशीन और मानव बुद्धि के बीच की खाई को पाटने का एक तरीका यह है कि हम मानव प्रतिभागियों पर संज्ञानात्मक प्रयोगों के माध्यम से प्राप्त संकेतों का उपयोग कृत्रिम प्रणालियों को डिजाइन करने में करें। यह थीसिस, अब से एआई-संचालित इंजीनियरिंग सिस्टम में मानव बुद्धि की नकल करने के लिए अगली पीढ़ी के सहयोगी मॉडल विकसित करने के लिए संज्ञानात्मक प्रक्रियाओं के विभिन्न पहलुओं की खोज में पर्याप्त प्रयासों की आवश्यकता को प्रेरित करता है।

Contents

| | |
|---|--------------|
| Certificate | iii |
| Acknowledgements | v |
| Abstract | vii |
| List of Figures | xvii |
| List of Tables | xxiii |
| 1 Introduction | 1 |
| 1.1 Introduction | 1 |
| 1.2 Literature Survey | 3 |
| 1.2.1 Optical Character Recognition | 3 |
| 1.2.2 Recognition using CNNs and Attention Models | 5 |
| 1.2.3 Explaining the Deep Networks | 6 |
| 1.2.4 Object and Character Recognition by Humans | 8 |
| 1.2.5 Eye-tracking Research | 11 |
| 1.3 Motivation | 14 |
| 1.4 Objectives and Scope | 14 |
| 1.5 Ethics clearance for human experiments | 15 |
| 1.6 Thesis Layout | 16 |

| | | |
|----------|---|-----------|
| 2 | Unlocking Reading Behaviors and Distorted Character Recognition using Eye-tracking | 19 |
| 2.1 | Introduction | 19 |
| 2.2 | Understanding Reading Behaviours | 20 |
| 2.3 | Eye-tracking experiment-1: Understanding Reading Behaviors | 22 |
| 2.3.1 | Participant screening | 22 |
| 2.3.2 | Stimulus Design | 23 |
| 2.3.3 | Experiment Protocol | 23 |
| 2.3.4 | Hypothesis Testing | 24 |
| 2.4 | Results and Discussions - I | 25 |
| 2.4.1 | Effect of font type on fixation duration, number of fixations and total reading time, number of regressions | 25 |
| 2.4.2 | Effect of Font Type on Reading Comprehension | 28 |
| 2.4.3 | Cognitive Engagement Leads to better Comprehension | 29 |
| 2.5 | Unlocking the Mechanisms of Distorted Character Recognition | 30 |
| 2.6 | Eye-tracking experiment-2: Distorted Character Recognition | 32 |
| 2.6.1 | Stimulus Design | 32 |
| 2.6.2 | Experimental Procedure | 33 |
| 2.7 | Results and Discussions - II | 34 |
| 2.7.1 | Recognition of Distorted Characters | 34 |
| 2.7.2 | Delay in Character Recognition explained through Eye-gazes | 35 |
| 2.8 | Summary | 37 |
| 3 | Understanding Character Recognition using Visual Explanations | 39 |
| 3.1 | Introduction | 39 |
| 3.2 | Related works: Explaining Deep Networks | 41 |
| 3.3 | Eye-tracking Experiment: Understanding the Strategies used for Character Recognition by Humans | 43 |

| | | |
|----------|---|-----------|
| 3.3.1 | Stimulus Preparation | 43 |
| 3.3.2 | Experimental protocol | 44 |
| 3.3.3 | Eye-tracking data processing | 45 |
| 3.4 | Eye-fixations Explain Character Recognition by Humans | 46 |
| 3.5 | Generating Explanations for Model’s Decision | 48 |
| 3.5.1 | Model Selection and Dataset Description | 49 |
| 3.5.2 | Grad-CAM and its Limitations | 50 |
| 3.5.3 | Proposed Method of Visualization - Modified Grad-CAM | 53 |
| 3.6 | Comparing Visual Explanations by Humans and Model | 55 |
| 3.7 | Visual Explanations Guided Attention Model (VEGAM) | 56 |
| 3.7.1 | Training the VEGAM model | 57 |
| 3.7.2 | Aligning Model’s Focus Improves Performance | 58 |
| 3.7.3 | Limitations of using Visual Explanations for Training | 62 |
| 3.8 | Discussions | 64 |
| 3.9 | Summary | 66 |
| 4 | Character Recognition using Attention Models Inspired by Eye-fixations | 67 |
| 4.1 | Introduction | 67 |
| 4.2 | Related Works | 68 |
| 4.3 | Deeply Supervised Attention Model | 69 |
| 4.3.1 | Model Architecture | 69 |
| 4.3.2 | Training the Proposed Model | 71 |
| 4.3.3 | Dataset | 71 |
| 4.3.4 | Ablation Experiments | 71 |
| 4.3.5 | Classification Performance by Proposed Model | 72 |
| 4.3.6 | Limitations of Deeply Supervised Model | 73 |
| 4.4 | Collaborative Attention Model | 74 |
| 4.4.1 | Visual Attention Map | 75 |

| | | |
|----------|---|-----------|
| 4.4.2 | Network’s Spatial Attention Map | 76 |
| 4.4.3 | Human-Machine Collaborative Attention Map | 77 |
| 4.4.4 | Experimental Details | 78 |
| 4.4.5 | Ablation Studies | 79 |
| 4.5 | Comparative Analysis using Classification Performance and Visualization Maps | 82 |
| 4.6 | Generalization ability | 85 |
| 4.7 | Summary | 86 |
| 5 | Investigation of Higher Level Visual Perception | 89 |
| 5.1 | Introduction | 89 |
| 5.2 | Bubble Technique | 90 |
| 5.2.1 | Stimulus preparation | 91 |
| 5.2.2 | Behavioral Experiment-1 | 92 |
| 5.2.3 | Computational Experiment | 93 |
| 5.3 | Results and Discussions | 93 |
| 5.3.1 | Comparing Recognition Performance of Humans and Computa- tional Model | 93 |
| 5.3.2 | Superior Recognition Performance in Humans | 94 |
| 5.4 | Investigation of High-level Visual Perception | 95 |
| 5.4.1 | Proposed RISE sequence | 95 |
| 5.4.2 | Behavioral Experiment-2 | 96 |
| 5.4.3 | Computational Experiment | 97 |
| 5.4.4 | Recognition of RISE Frames by Humans and Model | 98 |
| 5.4.5 | Comparing Recognition onsets | 99 |
| 5.4.6 | Role of Visual Mental Imagery in Recognition | 100 |
| 5.4.7 | Mental Imagery Assists Recognition | 103 |
| 5.5 | Mental Imagery through Computational Model | 104 |

| | | |
|----------|---|------------|
| 5.5.1 | Siamese Network | 104 |
| 5.5.2 | Early onset using Siamese | 107 |
| 5.6 | Summary | 108 |
| 6 | Contributions, Conclusions and Future Work | 111 |
| 6.1 | Contributions | 111 |
| 6.2 | Conclusions and Future Scope | 112 |
| | Bibliography | 115 |
| | Publications | 141 |
| 1 | Publications from PhD Work | 141 |
| 1.1 | Conferences | 141 |
| 1.2 | Journals | 142 |
| 2 | Awards, Recognitions for the PhD work | 142 |
| 3 | Publications from Collaborative Works | 142 |
| | Biography | 145 |
| | Glossary | 147 |
| 1 | Eye-tracking technology | 147 |
| 1.1 | Types of eye-movements | 148 |
| 1.2 | Algorithm for Fixation Identification | 149 |
| 2 | Model Evaluation Metrics | 149 |

List of Figures

| | | |
|-----|--|----|
| 1.1 | (a) Tobbi T120 eye-tracker, (b) Schematic of a 9-point calibration screen. One point (circle) is presented at a given time for a short duration and the participant is expected to focus at the center of that circle. | 12 |
| 1.2 | Gaze plot generated during reading. The circle shows fixations, where readers gaze at particular location for certain time duration. The line joining two fixations shows a saccade which indicates fast and rapid movement of eyes. The diameter of the circle varies according to fixation duration and the number denotes the sequence of fixation. | 13 |
| 2.1 | (a) Different parts of the character ‘क’; (b) Devanagari character ‘क’ written in (i) Kokila, (ii) Aparajita, (iii) Nirmala Font | 23 |
| 2.2 | Experimental Protocol; In each phase, a different set of document is presented | 24 |
| 2.3 | Gaze plots corresponding to documents written in (a) Kokila, (b) Aparajita, (c) Nirmala Font | 27 |
| 2.4 | (a) Effect of font type on Average fixation duration, (b) Effect of font type on the average number of fixations | 27 |
| 2.5 | Effect of font type on reading comprehension | 29 |
| 2.6 | (a) Some samples of Handwritten characters, (b) Division of characters in different parts, (c) Distorted characters at different distortion levels | 32 |
| 2.7 | Block diagram of the experimental procedure | 34 |

| | | |
|-----|---|----|
| 2.8 | (a), (b), (c) Recognition of characters at different distortion levels, (d) Heat-map of eye-fixations overlaid on the distorted characters | 36 |
| 3.1 | (a) Latin character ‘A’ and (b) Devanagari character ‘अ’ written in different forms, styles | 41 |
| 3.2 | (a) The characters are manually segmented from every word, (b) These segmented characters are processed- (i) Original character, (ii) Binarized character,(iii) Centered character | 44 |
| 3.3 | Randomly selected sample as a representative for each class of (a) Devanagari character and (b) Latin Character, (c) Participant sitting in front of the eye-tracker, (d) Stimulus presentation sequence. | 45 |
| 3.4 | Fixations on different character regions reveal character identity. (i) Input character image, (ii) Fixation map for unrecognized or misclassified character, (iii) Fixation map for correctly classified characters. | 48 |
| 3.5 | Schematic of the baseline model with $C_1, C_2 \dots C_6$: the convolutional layers, L : the linearization (i.e. vectorization) of the map to 1D; FC : the fully-connected layer. | 50 |
| 3.6 | Generation of class activation maps (visualization maps) by (a) Conventional Grad-CAM[1] and (b) Our method. The samples where Grad-CAM fails and our method generates the maps are highlighted by dotted yellow squares. | 52 |
| 3.7 | (a) Initial weight distribution, (b) Distribution of weights after training . . . | 55 |

| | | |
|------|---|----|
| 3.8 | (a) Schematic of proposed model: VEGAM, G: Gradient of the class score w.r.t. activations ‘A’ of the penultimate layer, (b) Comparative analysis of the visualizations (i)Input image, (ii)Visualization map for the baseline model which is unable to classify the character correctly, (ii)Human fixation map, (iii)The character getting correctly classified when VEGAM model focuses on the similar regions focused by the humans which is also shown in the visualization | 57 |
| 3.9 | (i)Input image, (ii)Fixation map, (iii)Visualization map for baseline model, (iv)Visualization map for proposed model VEGAM. The samples which are misclassified by baseline model are getting correctly classified by VEGAM. | 60 |
| 3.10 | (i) Input image, (ii) Fixation map, (iii) Visualization map for baseline model, (iv) Visualization map for proposed model VEGAM. The confidence corresponding to true class improves when the model is trained using fixation maps. | 61 |
| 3.11 | Training the model with optimizing CE and MSE loss iteratively | 63 |
| 3.12 | Understanding network dynamics while training iteratively with CE and MSE loss | 63 |
| 4.1 | Schematic of Deeply supervised Model | 70 |
| 4.2 | Visualization maps by respective models generated for few samples | 73 |
| 4.3 | Importance of Para-foveal regions in correct recognition depicted by respective visualization maps and fixation maps. | 74 |
| 4.4 | Schematic of Collaborative Human-Machine Attention Module | 78 |
| 4.5 | Placement of module in the network. Here, the attention module is our proposed module | 79 |
| 4.6 | The visualization maps demonstrating the importance of both fixation maps and network attention maps | 82 |
| 4.7 | Visualizations for few samples generated for respective models | 84 |

| | | |
|-----|--|-----|
| 5.1 | (a) Input image, (b) Gaussian Mask corresponding to 5, 10, 15, 20, 25, 30 bubbles (starting from top), (c) Stimulus image generated after passing through the corresponding Gaussian mask. | 92 |
| 5.2 | Stimulus presentation sequence | 93 |
| 5.3 | Recognition performance by humans and model | 94 |
| 5.4 | RISE sequence for a character क. As we can observe, the character ‘क’ seems to be evolved from noise. | 96 |
| 5.5 | Stimulus presentation sequence for experiment 1. The sequence is presented in order i.e. from highly scrambled to fully coherent one. Every stimulus image (frame) is followed by a question ‘whether the frame is recognized or not’. Participant has to respond by pressing appropriate keys and also verbalizing the response | 97 |
| 5.6 | Recognition response by the humans and the model to an increase in information for the Devanagari characters. The RISE frames are given as a testing samples to the model trained with handwritten samples, we observed that humans require minimum information for recognition compared to model. Humans identify the characters earlier as compared to model. Once a RISE sequence frame is recognized, the subsequent frames having more information are recognized simultaneously. Thus, we get the step-like response. Model relies on pixels level information. As a result we can see increase in confidence (CF) with increase in information. | 99 |
| 5.7 | Recognition onsets for different RISE sequences. When the RISE frames are given as a testing samples to the model trained with handwritten samples, we observed that humans require minimum information for recognition. Humans identify the characters earlier as compared to model. | 100 |
| 5.8 | Stimulus presentation sequence for experiment 2 | 101 |

| | | |
|------|--|-----|
| 5.9 | Recognition onsets for RISE sequence. (a) When the RISE sequence 1 has been presented to participant P1, the 12 th frame is recognized. (b) When the same sequence is repeated, the same participant identified the character at 8 th Frame. We call these two recognition time points as first and second onset of recognition for sequence presented for first and second time respectively. (c) The first and second onsets are given in the table. To compare whether there is a significant difference between first and second onset, we have aligned the onsets w.r.t. first onset. Un-aligned first and second onsets are shown in (d). After aligning the onsets with first onset for all sequences, we observe a cluster being formed for second onsets. (e) We performed the same process for all the participants for all the sequences. The second onset of recognition occurs earlier to first one and the difference between the two is significant ($p < 0.05$). | 102 |
| 5.10 | Schematic of Siamese Network | 105 |
| 5.11 | Verification phase. When images belong to same class the distance is near to 0 when they belong to different classes the distance is near to 1 | 106 |
| 5.12 | 12-way one shot learning. Encircled samples joined by a dotted line should have maximum similarity | 107 |
| 5.13 | Recognition onsets for humans, LeNet-5 and Siamese model. Siamese model makes the onset near to that of humans for most of the characters. | 108 |

List of Tables

| | | |
|-----|--|----|
| 2.1 | Understanding the processing of the Devanagari characters through eye fixations | 37 |
| 3.1 | Classification performance on testing data | 59 |
| 4.1 | Classification performance on testing samples by introducing fixation maps as supervisory input at different intermediate layers | 72 |
| 4.2 | Classification performance on testing samples | 73 |
| 4.3 | Comparison of different spatial attention methods for Network’s Spatial Attention | 80 |
| 4.4 | Combining Human and Network Attention map | 80 |
| 4.5 | Comparison of network’s performance with and without Fixation map | 81 |
| 4.6 | Comparison with eye-gaze based models | 84 |
| 4.7 | Classification performance (accuracy of recognition %) on Distorted, Hand-written and Transformed Devanagari characters | 85 |