

**ADVANCED DEEP LEARNING TECHNIQUES  
FOR FINGERPRINT PREPROCESSING**

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**ADVANCED DEEP LEARNING TECHNIQUES  
FOR FINGERPRINT PREPROCESSING**

*by*

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**Submitted**

**in fulfilment of the requirements of the degree of Doctor of Philosophy  
to the**



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# Certificate

This is to certify that the thesis titled **ADVANCED DEEP LEARNING TECHNIQUES FOR FINGERPRINT PREPROCESSING** being submitted by **Ms. INDU JOSHI** for the award of **Doctor of Philosophy in Computer Science and Engineering** is a record of bona fide work carried out by her under my guidance and supervision at the **Department of Computer Science and Engineering, Indian Institute of Technology Delhi**. 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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*Dedicated to my beloved father, who always dreamt  
that I become a professor someday. This is for you,  
papa!*

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# Abstract

The success of deep learning based models in image processing applications promotes their use in fingerprint preprocessing. However, poor generalization on unseen data and black box behaviour are the general limitations of deep models. Both these limitations of deep models are inherent to state-of-the-art fingerprint preprocessing models as well. Through this thesis, we exploit advanced deep learning techniques, namely *adversarial learning*, *attention mechanism* and *uncertainty estimation* for fingerprint preprocessing. We demonstrate that adversarial learning and attention mechanism help fingerprint preprocessing models to *generalize* on unseen, disparate sensing and acquisition techniques. We also illustrate that uncertainty estimation introduces *interpretability* in fingerprint preprocessing models such that a human operator can understand when the model is likely to make a mistake. The first three contributions of this thesis propose deep learning techniques that ensure improved generalization ability of fingerprint preprocessing models. The first contribution proposes a *generative adversarial network* for fingerprint enhancement which significantly outperforms state-of-the-art and serves as an efficient backbone network for fingerprint enhancement. Subsequently, we propose to utilize *channel-level attention* to boost the generalization ability of state-of-the-art fingerprint enhancement models. Next, we observe the limitation of state-of-the-art ROI segmentation methods on new and unseen sensors. To address this, we propose a *recurrent adversarial learning* based model, which has improved generalization ability on new and unseen sensors without requiring human-annotated ROI for the unseen sensor. For the other two contributions, we work on introducing interpretability in deep learning based fingerprint preprocessing models. For this, we find *Monte Carlo Dropout* to be an effective method to quantify the model's confidence in prediction and improve the representation ability of the baseline model. Finally, we estimate *data uncertainty* in fingerprint preprocessing to quantify the noise present in fingerprint images and demonstrate its usefulness in promoting noise-aware fingerprint preprocessing.

## सार

उंगलियों के निशानों के पूर्व प्रसंस्करण अनुप्रयोगों में डीप लर्निंग आधारित मॉडल की सफलता उंगलियों के निशानों के पूर्व प्रसंस्करण में उनके उपयोग को बढ़ावा देती है। हालांकि, अनदेखी डेटा और ब्लैक बॉक्स व्यवहार पर खराब सामान्यीकरण डीप मॉडल की सामान्य सीमाएं हैं। डीप मॉडल की ये दोनों सीमाएं अत्याधुनिक उंगलियों के निशानों के पूर्व प्रसंस्करण मॉडल में भी अंतर्निहित हैं। इस थीसिस के माध्यम से, हम उन्नत डीप लर्निंग तकनीकों का फायदा उठाते हैं, जैसे कि प्रतिकूल शिक्षा, ध्यान तंत्र और उंगलियों के निशानों के पूर्व प्रसंस्करण के लिए अनिश्चितता का अनुमान। हम प्रदर्शित करते हैं कि प्रतिकूल शिक्षा और ध्यान तंत्र उंगलियों के निशानों के पूर्व प्रसंस्करण मॉडल को अनदेखी, असमान संवेदन और अधिग्रहण तकनीकों पर सामान्य बनाने में मदद करता है। हम यह भी बताते हैं कि अनिश्चितता का अनुमान उंगलियों के निशानों के पूर्व प्रसंस्करण मॉडल में व्याख्यात्मकता का परिचय देता है जैसे कि एक मानव ऑपरेटर समझ सकता है कि मॉडल कब गलती कर सकता है। इस थीसिस के पहले तीन योगदान डीप लर्निंग तकनीकों का प्रस्ताव करते हैं जो उंगलियों के निशानों के पूर्व प्रसंस्करण मॉडल की बेहतर सामान्यीकरण क्षमता सुनिश्चित करते हैं। पहला योगदान उंगलियों के निशानों की वृद्धि के लिए एक जनरेटिव प्रतिकूल नेटवर्क का प्रस्ताव करता है जो अत्याधुनिक रूप से बेहतर प्रदर्शन करता है और उंगलियों के निशानों के एन्हांसमेंट के लिए एक कुशल बैकबोन नेटवर्क के रूप में कार्य करता है। इसके बाद, हम अत्याधुनिक उंगलियों के निशानों की एन्हांसमेंट मॉडल की सामान्यीकरण क्षमता को बढ़ावा देने के लिए चैनल-स्तरीय ध्यान का उपयोग करने का प्रस्ताव करते हैं। इसके बाद, हम नए और अनदेखी सेंसर पर अत्याधुनिक आरओआई विभाजन विधियों की सीमा का निरीक्षण करते हैं। इसे संबोधित करने के लिए, हम एक आवर्तक प्रतिकूल शिक्षण आधारित मॉडल का प्रस्ताव करते हैं, जिसने अनदेखी सेंसर के लिए मानव-एनोटेटेड आरओआई की आवश्यकता के बिना नए और अनदेखी सेंसर पर सामान्यीकरण क्षमता में सुधार किया है। अन्य दो योगदानों के लिए, हम डीप लर्निंग आधारित उंगलियों के निशानों के पूर्व प्रसंस्करण मॉडल में व्याख्यात्मकता शुरू करने पर काम करते हैं। इसके लिए, हम मोटे कार्लो ड्रॉपआउट को भविष्यवाणी में मॉडल के विश्वास को मापने और बेसलाइन मॉडल की प्रतिनिधित्व क्षमता में सुधार करने के लिए एक प्रभावी तरीका मानते हैं। अंत में, हम उंगलियों के निशानों की छवियों में मौजूद नॉइज़ को मापने के लिए उंगलियों के निशानों के पूर्व प्रसंस्करण में डेटा अनिश्चितता का अनुमान लगाते हैं और नॉइज़-जागरूक उंगलियों के निशानों के पूर्व प्रसंस्करण को बढ़ावा देने में इसकी उपयोगिता प्रदर्शित करते हैं।

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