Vishal Asnani

V-card

Phone: **+1 (517) 505-4249**
Email: asnanivi@msu.edu
Website: https://vishal3477.github.io/
LinkedIn: https://linkedin.com/in/vishal-asnani/
GitHub: https://github.com/vishal3477

OBJECTIVE

Media forensics professional determined to counter misinformation and deepfake media. Seeking an innovative role where advanced skills in analysis, detection, and verification can be applied to restore trust in visual information. Committed to leveraging cutting-edge technologies and collaborating with multidisciplinary teams for impactful solutions.

EDUCATION

Ph.D. In Computer Science and Engineering **| Jan. 2021-Current|**
Advisor: Dr. Xiaoming Liu
Michigan State University, East Lansing, USA
GPA: 3.75/4.0

B.E.(Hons.) Electronics and Instrumentation Engineering (Minor in Finance) **| Aug. 2015- May 2019|**
Birla Institute of Technology and Science, Pilani, India
CGPA: 8.01/10.0

PUBLICATIONS

- **Vishal Asnani**, Xi Yin, Tal Hassner, Xiaoming Liu, "MaLP: Manipulation Localization Using a Proactive Scheme," In Proceeding of IEEE Computer Vision and Pattern Recognition 2023.
- **Vishal Asnani**, Xi Yin, Tal Hassner, Sijia Liu, Xiaoming Liu, "Proactive Image Manipulation Detection," In Proceeding of IEEE Computer Vision and Pattern Recognition 2022.
- **Vishal Asnani**, Xi Yin, Tal Hassner, Xiaoming Liu, "Reverse Engineering of Generative Models: Inferring Model Hyperparameters from Generated Images" under review in IEEE Transactions on Pattern Analysis and Machine Intelligence 2022.

WORK EXPERIENCE

Adobe, San Jose, USA: Research Scientist Intern **| June. 2023- Aug. 2023 |**
- Research scientist intern in the **Cross-representation learning (XRL) team**.
- Working on the **novel problem** of **Causal Training Concept attribution** for the synthetic images generated by a generative model.
- The problem involves **attributing different artist's** concept images which influenced the generation of the synthetic images.
- We use a **proactive scheme** of embedding different **watermarks** into the images, to later **recover** these watermarks for attribution.

Texas Instruments, Bengaluru, India: Analog design intern **| Jul. 2018- Dec. 2018 |**
- Analog design intern in **Multiphase and Control solutions team**.
- Developed a Perl Script to create vector-based patterns for SWD and PMBus commands used in the test program.
- Patterns were appended to the test program beforehand, thereby saving test time.
- Efficient implementation of **SWD and PMBus patterns** saved approximately **74% execution time**.

PROJECTS

1. **Image manipulation Localization using proactive schemes.** **|May. 2022-Nov. 2022|**
   - A **novel proactive scheme** for image **manipulation localization**, MaLP, applicable to both face and generic images is proposed.
   - MaLP has a **two-branch architecture** to use both **local and global features** to learn templates in an unsupervised manner.
   - MaLP can be used as a **plug-and-play discriminator module** to fine-tune GMs to improve the quality of the generated images.
   - MaLP **outperforms State-of-The-Art (SoTA)** methods in manipulation localization and detection.
2. **Proactive scheme for image manipulation detection by adding learnable templates** **|May. 2021-Apr. 2022|**
   - A **novel proactive scheme** is proposed which encrypts a real image by adding a template from a **learnable template set**.
   - The **added template** is later **recovered** to perform image manipulation detection.
   - The template set is **learned** using defined **constraints** which incorporate properties including small magnitude, more high-frequency content, orthogonality, and classification ability
   - **Near-perfect** average precision is obtained for unseen Generative Models (GMs) compared to prior works.
   - The proposed framework is **more generalizable** to different GMs, showing an **improvement of 10%** average precision averaged across 12 GMs compared to prior works.
3. **Model Parsing: Reverse engineering of hyperparameters of generative models** **|Jul. 2020-Apr. 2022|**
   - A **novel** problem of **Model Parsing** is defined to develop a framework for **predicting** the **network architecture** and **loss functions** given a generated image.

- We estimate the **mean and deviation** for each GM using **two different parsers**: cluster parser and instance parser which are then combined as the final predictions.
- A network architecture super-set with **15 features** and a loss function type super-set with **10 features** were selected to represent every GM.
- 1000 images each for 116 generative models were collected to create a **new dataset,** and the experiments were conducted in the **leave-out** setting.
- The framework has an **L1 error** of **0.149** with **a p-value of 0.00045** for **continuous** type parameters and **71.8% F1-score** for **discrete** type parameters in **network architecture** prediction.
- **81.3% F1-score** for the type of **loss function** prediction was achieved.
- The method generalizes well to tasks of **deepfake detection** on the Celeb-DF benchmark and **image attribution** with an AUC of **74.60%** and **99.32%,** respectively, in both cases reporting results comparable with existing **SOTA**.

4. **Deepfake video detection model built using PyTorch** **|Feb. 2020-Apr. 2020|**
   - Implemented a machine learning model consisting of Convolution neural networks (CNN) followed by a recurrent neural network (RNN) for **deepfake detection**.
   - The **CNN-RNN model** would be able to detect whether a video is fake or real.
   - The frames were extracted using the MTCNN model, which was then passed into the CNN-RNN model, **trained** on the **Face-Forensics++** (FF++) dataset, and **tested** on the **FF++ and Celeb-DF** datasets.
   - The model achieves **98.2% AUC** on the FF++ dataset and **68.1% AUC** on the Celeb-DF dataset.

5. **Machine learning classifiers to classify news into different categories.** **|Mar. 2020-May 2020|**
   - **News category dataset** available on Kaggle was used to test **different classifiers classifying news** into different categories.
   - **Many classifiers** were tested like Multinomial Naïve Bayes, Multinomial Gaussian Bayes, K nearest neighbor, Decision trees, Linear Support vector machines, Multi-class logistic regression, Bagging, AdaBoost, and Recurrent neural network.
   - The models were tested on the **different trains: test split ratio** and **different hyperparameters** for each classifier.
   - Multinomial Gaussian Bayes, Multi-class logistic regression, and Linear Support vector machines performed better than other classifiers with an **accuracy of 75%.**

6. **Framework for information retrieval using PyTorch** **|Aug. 2019-Dec. 2019|**
   - Developed a framework for **binding and retrieving class-specific information** from image patterns using correlation filters.
   - The template-based framework works by **matching the template** with the **query pattern** of the same class.
   - Class-specific information is mapped to spatial translations applied to image patterns to generate a multi-peak correlation filter.
   - The **CMU PIE and FRGC databases** were used to study the relationship between the False class Information retrieval rate (FCIRR) and several peaks of the correlation filter.
   - FCIRR had an **inverse relationship** with several peaks. The **FCIRR for 30 peaks** was **0.02 for CMU PIE and 0.88 for FRGC**.

7. **Deep Learning model involving modified version of LSTM RNN** **|Jan. 2019-May 2019|**
   - Developed a deep learning framework involving two parameter-reduced variants of the **LSTM layer**.
   - The model was built using high-level Keras API in the Jupyter Notebook with the **UCI News Aggregator dataset**.
   - **1% increase** in accuracy was achieved in the model involving a modified LSTM layer compared to the standard LSTM layer.

TECHNICAL PROFICIENCY

Tools, Simulation, and Software Platforms

- TensorFlow, PyTorch, Keras, Numpy, Scikit-learn, Jupyter, OpenCV, CUDA, MATLAB and Simulink, GCS, Amazon Web Services (AWS), LabVIEW, Linux, CST Microwave studio, Cadence virtuoso, Microsoft-Visual Studio, Excel, Word and Powerpoint, Orcad PSpice, Labcentre Proteus, Eagle- PCB Design and Schematic Software, Xilinx Vivado Suite and SDK, FluidSim

Languages / Scripts

- Python, MATLAB, R, SQL, Perl, C, C++, Cascading Style Sheets (CSS), JavaScript, HTML, Verilog, VHDL, x86 Assembly Language, Arduino Programming

---

TALKS GIVEN

1. In-person talk given at Scale-AI headquarters in San Franscisco. The talk was focused on our work on reverse engineering of generative models. (Recording available on website)
2. Virtual talk given at Sacle-AI. The talk was focused on our work on proactive image manipulation detection. (Recording available on website)

RELEVANT COURSES PURSUED

- Computer Vision: Detectors and Descriptors, Optical Flow, Image segmentation, Tracking and object detection, Epipolar geometry.
- Machine learning: Regression, Classification, Dimensionality reduction, Sparse learning, Ensemble methods, Multi-task learning
- Pattern recognition and analysis: Bayesian classification, Estimating gaussian MLE parameters, Non-parametric density estimation.
- Deep Learning: Deep Neural Networks, Convolution Neural Networks, Recurrent Neural Networks, Sequence Models.
- Deep Learning specialization- deepleraning.ai by Andrew Ng (Coursera).
