Image Captioning and HashTag Generation

Project report submitted to
Indian Institute of Technology, Kanpur,
In partial fulfillment of the coursework
of

GenAI (CS787)
In
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by

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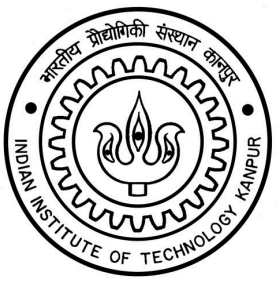

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Certificate

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Abstract

The “Image Captioning and Hashtag Generation” project utilizes advancements in deep learning, and multilingual natural language processing to automatically interpret visual content and express it in human-readable form. With the growing demand for accessible and engaging multimedia content, the ability to generate meaningful captions and relevant hashtags across multiple languages has become increasingly valuable. This system integrates cutting-edge architectures such as CNN-based feature extractors, LSTM and transformer-based language models, and multilingual embeddings to create a robust framework capable of understanding images and expressing their semantics in diverse linguistic forms.

The central components of the system include automatic caption generation and hashtag creation from input images in both **English and four major regional languages—Hindi, Tamil, Telugu, and Bengali**. By combining visual feature extraction using **VGG16** with sequence-generation models, the system produces grammatically coherent and contextually accurate descriptions. The multilingual hashtag generator further enhances accessibility and content visibility by predicting culturally and linguistically relevant tags tailored for different user groups.

In addition, the project explores an extended functionality that attempts to generate captions and hashtags even from **damaged or partially corrupted images**, improving the model’s applicability in real-world scenarios where image quality may be compromised.

Evaluation of the system is performed using the **BLEU score**, ensuring quantitative measurement of caption quality. The project is implemented using TensorFlow, CNN-based encoders, LSTM decoders, and transformer-enhanced NLP modules, combining the strengths of both visual and linguistic deep learning paradigms.

By offering multilingual support, hashtag optimization, and resilience to degraded images, the “Image Captioning and Hashtag Generation” system provides a comprehensive AI-driven solution for enhancing digital content creation, accessibility, and user engagement across diverse platforms.

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1. Introduction

1.1. Problem Statement

In the rapidly expanding digital world, a large amount of visual content is shared every day, yet most of it lacks proper captions and meaningful hashtags. Without these elements, images become less accessible, harder to understand, and difficult to search or classify on online platforms. Manually writing captions and selecting hashtags is time-consuming, inconsistent, and often limited by the creator's language skills, which reduces the overall visibility and impact of the content.

Another major challenge is multilingual accessibility. Many existing tools only support English, leaving a gap for users who prefer regional languages such as Hindi, Tamil, Telugu, or Bengali. This limits the reach and inclusiveness of digital content. Additionally, real-world images are not always clear—some may be blurred, damaged, or partially distorted, making it difficult for conventional models to produce accurate descriptions.

These issues highlight the need for an automatic system that can understand image content, generate simple and meaningful captions, and provide relevant hashtags in multiple languages. Such a solution would help improve accessibility, enhance user engagement, and support efficient content creation across different digital platforms.

1.2. Image Captioning and Hashtag Generation

To address the growing need for accessible and well-organized visual content, we developed an **Image Captioning and Hashtag Generation system** designed to interpret images and convert them into clear and meaningful text. The system aims to make image-based content easier to understand and share by automatically generating captions and relevant hashtags—even when the input image is slightly damaged or unclear. It supports both English and major regional languages such as Hindi, Tamil, Telugu, and Bengali, making it useful for a wide range of users.

Our system uses techniques from **deep learning, and natural language processing** to extract features from an image and produce descriptive sentences along with context-based hashtags. Models such as VGG16, LSTM, and transformer-based language generators work together to create captions that are simple, accurate, and closely related to the image content. The multilingual hashtag generation further helps improve content visibility across different digital platforms.

More than just a caption generator, this system acts as a helpful companion for content creators, students, and professionals who need quick and reliable descriptions of images. It reduces the time and effort required to manually write captions or think of suitable hashtags. With its ability to handle damaged images and support multiple languages, the system offers a smooth and efficient way to produce high-quality text for visual content, making digital communication more inclusive and easier to access.

2. Literature Review

In developing the Image Captioning and Hashtag Generation system, we reviewed several foundational research studies that explore the intersection of computer vision, sequence modeling, multilingual text generation, and image restoration. These studies provided essential insights into visual feature extraction, encoder–decoder architectures, optimization strategies, and techniques for handling damaged or incomplete images—each of which played an important role in shaping the methodology of our project.

Oriol Vinyals, Alexander Toshev, Samy Bengio, Dumitru Erhan (2015) introduced the "Show and Tell" model, one of the first end-to-end frameworks combining CNNs with LSTMs to generate natural language descriptions from images. Their work demonstrated how visual features from convolutional networks can be effectively translated into descriptive sentences using recurrent networks. Their experiments showed significant improvements in BLEU scores across datasets by learning directly from image–caption pairs, establishing a strong foundation for modern captioning systems

Kingma and Ba (2015) proposed the Adam optimizer, a widely used method for training deep learning models. Adam uses adaptive learning rates and moment estimates, making it suitable for large-scale and noisy gradient environments. Its efficiency and stability helped improve convergence during the training of deep captioning and multilingual text-generation models in our project

Hinton (2015) introduced the concept of knowledge distillation, a powerful approach to transfer the generalization capability of large, cumbersome networks into smaller models. This method uses soft targets produced by a high-capacity model to guide a smaller model, leading to improved performance with lower complexity. The idea of "soft knowledge transfer" influenced our multilingual caption and hashtag generation pipeline, helping create compact models without compromising quality

Liu (2018) proposed Partial Convolution for image inpainting, addressing the limitations of conventional convolutional networks when dealing with irregular holes or damaged regions. Their approach uses masked and renormalized convolutions that rely only on

valid pixels, enabling robust reconstruction of corrupted images. This technique inspired the damaged-image handling component of our project, where captions and hashtags are generated even from partially distorted visual inputs

Ronneberger (2015) introduced the U-Net architecture for biomedical image segmentation, combining downsampling and upsampling paths with skip connections. Its ability to extract fine-grained spatial features using very limited training data influenced the visual preprocessing stage of our system, particularly for enhancing feature quality in low-resolution or noisy images.

By integrating concepts from these studies—CNN–RNN captioning models, efficient optimization, model compression, partial convolution for damaged images, and robust feature extraction—we build a system capable of generating captions and hashtags in English and multiple regional languages. These insights collectively guided our approach toward producing accurate, context-rich descriptions even under challenging image conditions.

S. No.	Research Paper Title	Summary
1	*Show and Tell: A Neural Image Caption Generator* Publish Date: 20 April 2015 Published by: Oriol Vinyals, Alexander Toshev, Samy Bengio, Dumitru Erhan	**<u>Working Model</u>** • **Image Feature Extraction:** A deep CNN processes the image and converts it into a fixed-length feature vector that captures important objects and visual details. • **Sequence Generation:** An LSTM network uses the extracted visual features as input and generates captions word-by-word in natural language. • **Word Embeddings:** Each word is converted into a numerical embedding to help the model understand semantic

	Link: https://arxiv.org/pdf/1411.4555	similarities among words. • **End-to-End Training:** The CNN and LSTM are trained together to maximize the probability of producing the correct caption for each image. • **Beam Search Decoding:** During prediction, beam search is used to select the most meaningful and grammatically correct caption from multiple possible outputs. • **Evaluation Metric:** The model uses BLEU score to measure the accuracy of generated captions by comparing them with human-written sentences. **Challenges they have faced** • Difficulty in aligning visual features with meaningful language, since captions must describe objects, relationships, and activities accurately. • Limited high-quality caption datasets cause overfitting and reduce the model's ability to generalize. • The model struggles to generate completely new and diverse captions, often repeating common training phrases. • Caption quality is hard to evaluate because automatic metrics like BLEU sometimes do not match human judgment. • Training is computationally expensive due to the large CNN and LSTM components, requiring careful optimization.

2	*ADAM: A METHOD FOR STOCHASTIC OPTIMIZATION* Publish Date: 30 Jan 2017 Published by: Diederik P. Kingma, Jimmy Lei Ba Link: https://arxiv.org/pdf/1503.02531	**Working Model** • **Adaptive Learning Rates:** Adam computes separate learning rates for each parameter by using the first and second moment estimates of gradients. • **Moment Estimation:** It maintains an exponential moving average of gradients (first moment) and squared gradients (second moment) to stabilize updates. • **Bias Correction:** Since the moment values start at zero, Adam applies bias-correction to make early updates more accurate. • **Efficient Parameter Updates:** The algorithm updates parameters by dividing the corrected first moment by the square root of the corrected second moment. • **Handles Noisy Objectives:** The optimizer works well with noisy, sparse, or non-stationary gradients, making it suitable for large deep learning tasks. • **Low Memory Requirement:** Adam requires very little memory and is easy to implement, making it widely applicable across neural network models. **Challenges they have faced** • In some cases, Adam may converge slower or become unstable without proper hyperparameter tuning. • When the decay rate β_2 is very close to 1, the absence of bias correction can lead to extremely large and harmful update steps.

		• Adam may generalize worse than simpler optimizers like SGD in certain scenarios, especially on tasks requiring strong regularization. • The theoretical convergence properties depend heavily on specific conditions, making guaranteed performance difficult in non-convex problems. • Choosing proper learning rates and decay factors remains important, as incorrect settings can lead to divergence or poor minima.
3	*Distilling the Knowledge in a Neural Network* Publish Date: 9 March 2015 Published by: Geoffrey Hinton, Oriol Vinyals, Jeff Dean License: ISSN 1157-5896 Link: The Science and Information (SAI) Organization	**Working Model** • **Soft Target Generation:** A large "cumbersome" model or ensemble produces soft probabilities (soft targets) that capture richer information than hard labels. • **High-Temperature Softmax:** A higher softmax temperature is used to soften probability distributions, revealing similarities between classes. • **Knowledge Transfer:** A smaller model (student) is trained to match these soft targets, learning the generalization behavior of the larger model. • **Combined Training:** When true labels exist, the student is trained using a weighted combination of soft-target loss and hard-label loss. • **Model Compression:** The method compresses the performance of large

		ensembles into a compact, deployment-friendly model without losing much accuracy. • **Specialist Models:** In large datasets, individual "specialist" models focus on confusing class subsets, and their knowledge is also distilled into a generalist. **<u>Challenges they have faced</u>** • Distillation requires choosing an appropriate temperature; very high or very low temperatures reduce effectiveness. • Small models cannot perfectly match all knowledge of large ensembles, especially when the task has fine-grained distinctions. • Training specialists can lead to overfitting due to heavily biased class subsets. • Soft targets may ignore very negative logits, which sometimes carry useful information about class structure. • Ensemble-based soft target generation is computationally expensive for very large models. • Balancing the weight between hard and soft target losses is sensitive and requires careful tuning.
4	*Image Inpainting for Irregular Holes Using Partial Convolutions* Publish Date: 15 December 2018 Published by: Guilin Liu	**<u>Working Model</u>** • **Masked Convolution:** The model uses partial convolutions that operate only on valid (non-masked) pixels, ignoring damaged or missing regions. • **Automatic Mask Updating:** After each partial convolution, the mask is updated so that newly filled regions become valid for

	Fitsum A. Reda Kevin J. Shih Ting-Chun Wang Andrew Tao Bryan Catanzaro Link: https://arxiv.org/pdf/1804.07723	the next layer. • **U-Net Architecture:** A U-Net–like encoder–decoder structure is used, with skip connections to maintain fine details during reconstruction. • **Boundary Handling:** Partial convolutions naturally replace padding with valid-mask padding, preventing border artifacts. • **Loss Functions:** A combination of pixel loss, perceptual loss, style loss, and total variation loss is used for smooth and realistic inpainting. • **Irregular Mask Robustness:** The model is trained on thousands of irregular hole shapes, enabling it to handle complex, non-rectangular missing areas. • **Single-Pass Reconstruction:** Unlike earlier methods, the network can produce clean inpainted images in a single forward pass without extra post-processing. **Challenges they have faced** • Traditional convolution layers depend heavily on placeholder values inside holes, causing texture mismatch and color inconsistencies. • Earlier inpainting methods struggle with irregular or edge-touching holes, often overfitting to rectangular masks. • Post-processing steps used in old models (like Poisson blending) are expensive and sometimes fail to remove artifacts. • Some images with very thin or repetitive patterns (like grids or bars) remain difficult to

		reconstruct accurately. • Training requires careful mask design; poor mask generation can lead to weak generalization on complex missing regions. • Very large holes still produce imperfect results, as too much information is missing for reliable reconstruction.
5	*U-Net: Convolutional Networks for Biomedical Image Segmentation* *Publish Year: 18 May 2015* *Published by: Olaf Ronneberger, Philipp Fischer, and Thomas Brox* *Link: https://arxiv.org/abs/1505.04597*	**Working Model** • **Encoder–Decoder Structure:** The model uses a contracting path to capture context and an expanding path to enable precise localization. • **Downsampling Path:** Repeated 3×3 convolutions and max-pooling layers extract deep features while reducing spatial resolution. • **Upsampling Path:** Up-convolutions and feature concatenation with encoder layers help recover lost spatial details. • **Skip Connections:** Features from the encoder are directly copied to the decoder to preserve fine-grained information. • **No Fully Connected Layers:** The network is fully convolutional, allowing it to handle images of any size. • **Data Augmentation:** Elastic distortions and transformations are heavily used to train the model with very few labeled samples. • **Fast Segmentation:** The architecture

		produces pixel-wise segmentation maps efficiently, suitable for large biomedical images. **<u>Challenges they have faced</u>** • Requires careful initialization; poor initialization causes unstable activations in deeper layers. • Precise boundary segmentation is difficult when objects touch or overlap closely. • Works heavily with small datasets, so strong data augmentation is essential to prevent overfitting. • Crop-and-copy operations increase memory usage, especially with large feature maps. • Without proper weight balancing, the model may struggle with class imbalance in segmentation datasets. • Downsampling can cause loss of fine details if skip connections are not effectively used.
6	*Attention Is All You Need* *Publish Year: 2 August 2023* *Published by: Ashish Vaswani, Llion Jones, Noam Shazeer, Aidan N. Gomez, Niki Parmar, Jakob Uszkoreit, Łukasz Kaiser, Illia Polosukhin*	**<u>Working Model</u>** • **Self-Attention Mechanism:** The model relies entirely on self-attention to capture relationships between tokens, removing the need for RNNs or CNNs. • **Encoder–Decoder Structure:** The network consists of stacked encoder and decoder layers, each containing multi-head attention and feed-forward blocks. • **Multi-Head Attention:** Queries, keys, and values are processed through multiple

	Link: *https://arxiv.org/pdf/1706.03762*	attention heads to learn different contextual representations in parallel. • **Positional Encoding:** Since the model has no recurrence, sinusoidal positional encodings are added to embeddings to retain information about word order. • **Parallel Processing:** All input tokens are processed simultaneously, enabling faster training compared to sequential RNN models. • **Masked Decoder Attention:** The decoder uses masked attention to ensure that each generated token depends only on earlier tokens in the sequence. • **Feed-Forward Layers:** Each encoder and decoder layer includes a position-wise feed-forward network to enhance non-linear feature transformation. • **Efficient Training:** The Transformer achieves high translation quality while reducing training time using parallel computation **Challenges they have faced** • Requires careful initialization; poor initialization causes unstable activations in deeper layers. • Precise boundary segmentation is difficult when objects touch or overlap closely. • Works heavily with small datasets, so strong data augmentation is essential to prevent overfitting.

		• Crop-and-copy operations increase memory usage, especially with large feature maps. • Without proper weight balancing, the model may struggle with class imbalance in segmentation datasets. • Downsampling can cause loss of fine details if skip connections are not effectively used.

3. Proposed Models and Techniques

This section describes the complete architecture and methodologies used in the development of the Image Captioning and Hashtag Generation System. The goal of the system is to automatically generate meaningful captions and relevant hashtags for images in English and four regional languages: Hindi, Tamil, Telugu, and Bengali. The project integrates multiple deep learning methods, including Convolutional Neural Networks (CNNs), sequence generation techniques using LSTM and GRU, Transformer-based text models, Knowledge Distillation, multilingual BERT (mBERT-50), U-Net for damaged image handling, and natural language processing tools such as NLTK. All components are implemented using TensorFlow.

3.1 CNN-Based Image Understanding

Objective

To convert raw images into a structured representation that captures objects and their relationships, enabling accurate caption and hashtag generation.

3.1.1 Image Feature Extraction Using VGG16

The system uses VGG16, a deep convolutional neural network pretrained on ImageNet, as the primary feature extractor. VGG16 processes the input image and transforms it into a 4096-dimensional feature vector. This vector contains the semantic and structural information needed for caption generation.

VGG16 captures information at three levels:

1. Low-level features such as edges, gradients, and basic textures.
2. Mid-level features such as object parts and shapes.
3. High-level features such as objects, context, and overall scene structure.

Using a pretrained CNN offers several advantages. It provides transfer learning benefits, reduces training time, increases accuracy, and improves generalization even on small datasets.

3.1.2 Damaged Image Handling Using U-Net

To support caption generation from corrupted or partially missing images, the system includes a U-Net-based image reconstruction module. U-Net follows an encoder–decoder architecture. The encoder captures the global context of the image while the decoder reconstructs missing or distorted regions.

Skip connections ensure that fine details lost during downsampling are restored during upsampling. As a result, the reconstructed output is more complete and clear. This refined image is then passed into VGG16 for feature extraction.

U-Net improves the system's robustness by restoring blurred, scratched, or incomplete images, ensuring the captioning model receives high-quality visual input.

3.1.3 Why CNN Instead of Traditional Computer Vision

Traditional computer vision techniques use manually designed features and fail to understand complex scenes, object interactions, and contextual meaning. CNNs learn these features automatically by training on millions of images. They are more accurate, more flexible, and integrate more effectively with NLP models. Therefore, CNNs serve as the foundation for visual understanding in the project.

3.2 Caption Generation Models

The captioning module uses a hybrid approach combining Transformer-based encoders and recurrent decoders such as LSTM and GRU. This combination ensures both strong contextual understanding and smooth sentence generation.

3.2.1 Transformer Encoder for Context Processing

Transformers are used to model long-range dependencies within the sentence. The encoder refines the visual features by using attention mechanisms to understand how different parts of the sentence relate to each other.

Key components used in the Transformer encoder include multi-head self-attention, positional encoding, feed-forward layers, and normalization layers.

These components help the model produce more fluent and coherent captions.

3.2.2 LSTM-Based Decoder for Sentence Generation

The LSTM decoder generates captions word-by-word using the visual features from VGG16 and the contextual information from the Transformer. LSTMs handle long-term dependencies and ensure grammatical correctness and sentence flow.

3.2.3 GRU-Based Decoder for Lightweight Captioning

The GRU decoder is used as an alternative lightweight model. GRUs require fewer parameters than LSTMs, train faster, and work efficiently for multilingual captioning. Using both LSTM and GRU allows a balance between speed and accuracy.

3.3 Multilingual Caption and Hashtag Generation

The system supports the generation of captions and hashtags in English, Hindi, Tamil, Telugu, and Bengali.

3.3.1 Multilingual Caption Generation Using mBART-50

After generating the English caption, mBART-50 (Multilingual BERT) is used to translate it into the four regional languages. mBART-50 maps words from multiple languages into a shared embedding space, ensuring that meaning is preserved during translation.

This approach improves fluency, contextual accuracy, and readability of captions in all target languages.

3.3.2 Hashtag Generation Using NLTK and mBART

Hashtags are generated through a two-step process:

1. Using NLTK to extract keywords. This includes tokenization, stopword removal, part-of-speech tagging, and keyword selection.

2. Passing these keywords through mBERT-50 to translate them into regional languages and convert them into culturally and linguistically accurate hashtags.

3.4 Knowledge Distillation for Model Optimization

Knowledge Distillation is used to reduce the size of the model and improve execution speed. In this approach, a large teacher model generates soft labels, and a smaller student model learns to mimic these soft labels.

This process reduces memory usage, increases inference speed, and makes multilingual caption generation more efficient without sacrificing quality.

3.5 Text Processing Using NLTK

NLTK is used to process text and prepare it for both captioning and hashtag extraction. NLTK performs tokenization, lemmatization, stopword removal, and part-of-speech tagging. This ensures that the text passed to the model is clean, structured, and meaningful.

3.6 Complete System Workflow

Training Phase

1. Input images are preprocessed.
2. Damaged images are reconstructed if necessary. (Couldn’t done)
3. Features are extracted using VGG16.
4. Transformer encoders refine visual features.
5. LSTM or GRU decoders generate captions in English.
6. Captions are translated into regional languages using mBART-50.
7. Hashtags are generated using NLTK and mBART.
8. Knowledge Distillation reduces the model size.
9. BLEU score is used for evaluation.

Prediction Phase

1. A new image is input into the system.
2. The image is preprocessed and reconstructed if needed.
3. Features are extracted using the CNN.
4. An English caption is generated.
5. Translations are produced using mBART-50.
6. Hashtags are generated.
7. Final outputs are displayed.

4. Implementation Details

This section describes the complete implementation workflow of the Image Captioning and Hashtag Generation project. The project is designed using four independent pipelines, each focusing on a different aspect of image understanding, caption generation, multilingual expansion, hashtag prediction, and damaged image recovery. The purpose of building multiple pipelines is to thoroughly analyze different deep learning strategies and compare their performance across a variety of image types and use cases.

The implementation covers dataset preparation, model training, reconstruction of damaged images, multilingual text generation, and hashtag prediction. Furthermore, all trained models are uploaded to **HuggingFace**, enabling public use, reproducibility, and future extension by other researchers.

4.1 Overall System Flowchart

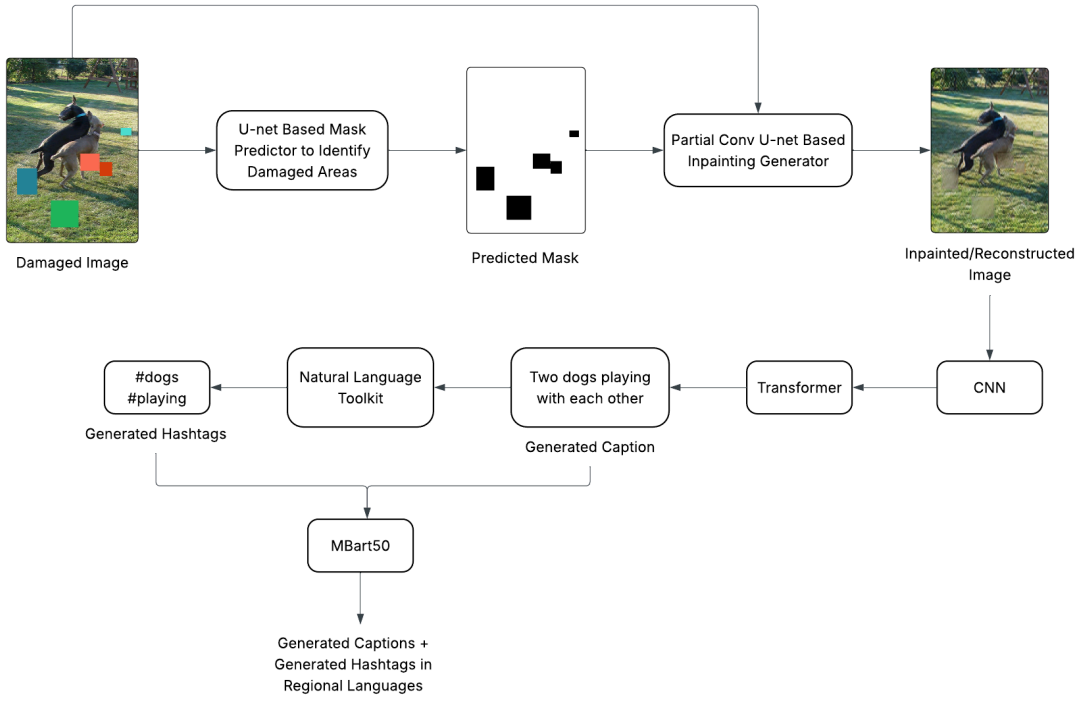


Fig 1: Overall System Flowchart

The final workflow begins with an image, reconstructs it if needed, *[Reconstruction part is still in progress due to less accuracy]* processes it through CNN encoders, passes representations to captioning or hashtag-generation modules, performs multilingual translation using mBART, and outputs captions/hashtags in English and four regional languages.

4.2 Pipeline Overview

The system is composed of four independent pipelines:

1. **Pipeline 1 – Knowledge Distillation on CNN (Base Concept)**

From VGG16 (Teacher) to Small CNN (Student) integrated into LSTM captioning.

2. **Pipeline 2 – CNN + Transformer + NLTK + mBART**
   (Multilingual Captioning and Hashtag Generation)

3. **Pipeline 3 – CNN + GRU** (Hashtag Generation Using Generative GRU Network)

4. **Pipeline 4 – Damaged Image Reconstruction (U-Net Mask Prediction + PartialConv U-Net)**
   (Implemented entirely using PyTorch) (Not able to implement completely with good accuracy)

Each pipeline is detailed in the following sections.

4.3 Pipeline 1: Knowledge Distillation on CNN (Base Paper Implementation)

This pipeline implements the knowledge distillation concept inspired by the original Show-and-Tell architecture. The primary objective is to compress the visual encoder to make captioning more efficient.

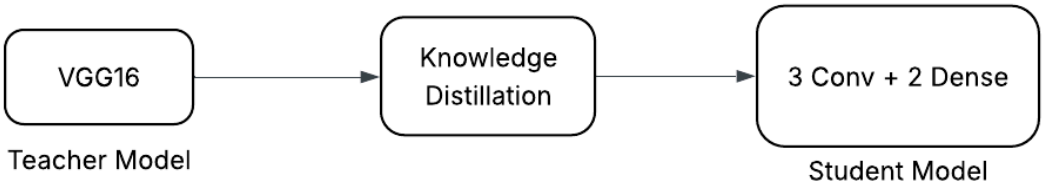


Fig 2: Knowledge Distillation Flowchart

4.3.1 Teacher Model (VGG16)

The pretrained VGG16 model extracts high-level visual features from input images.

- Input: Raw image
- Output: 4096-dimensional feature vector
- Advantage: Strong feature representation but computationally heavy
- Limitation: High parameter count makes it unsuitable for low-resource devices

4.3.2 Distillation Phase

Knowledge distillation is applied to transfer the knowledge of VGG16 into a smaller, custom CNN.

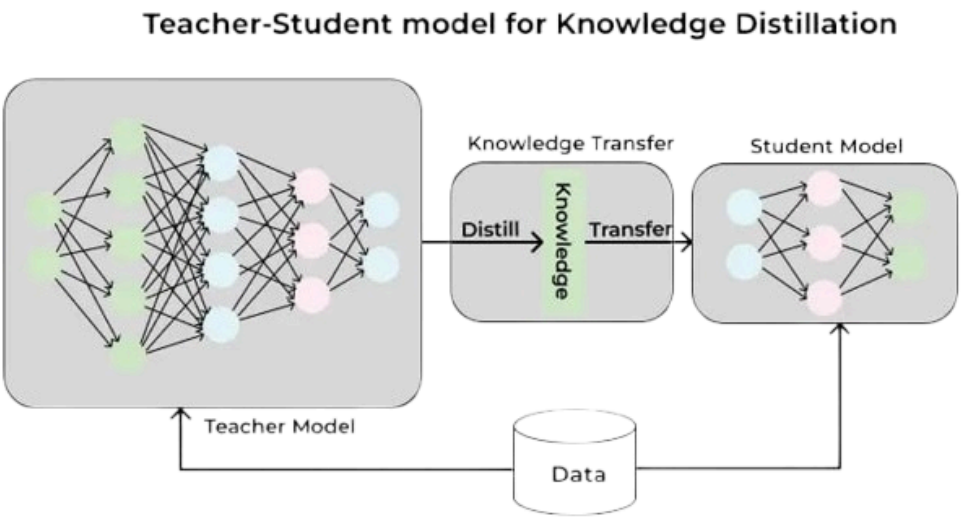


Fig 3: Teacher Student Diagram

Distillation Process

- The teacher CNN generates soft feature distributions.
- A student CNN is trained to mimic these distributions.
- Loss function includes:
    - Mean Squared Error (MSE)
    - KL Divergence Loss

Benefit

The student model learns to approximate VGG16's feature extraction behavior using far fewer parameters.

4.3.3 Student CNN Model Architecture

The final distilled student network consists of:

- 3 Convolutional layers
- 2 Dense layers
- Produces a feature vector compatible with caption decoder

This reduces the model size significantly while maintaining accuracy.

4.3.4 Caption Generation Using LSTM

The compressed CNN output initializes an LSTM decoder that generates captions sequentially.

Example output:
“A dog is running through a field.”

This pipeline matches the base research approach but is far more efficient due to model compression.

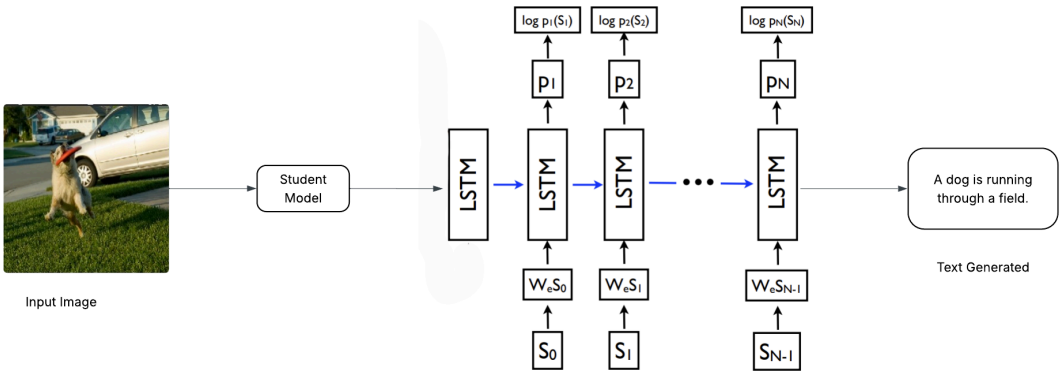


Fig 4: Caption Generation for Student Model

4.4 Pipeline 2: CNN + Transformer + NLTK + mBART (Proposed Pipeline 1)

This pipeline represents the **main proposed architecture**, enabling multilingual captioning and hashtag generation.

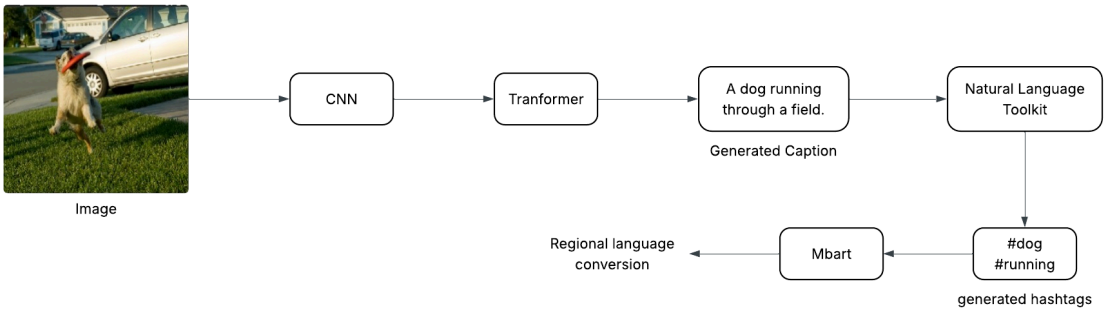


Fig 5: Pipeline 2 Flowchart

4.4.1 CNN Feature Extraction

Either VGG16 or the distilled student CNN is used.
Output: Dense feature embedding.

4.4.2 Transformer Encoder

A Transformer encoder enhances contextual understanding using:

- Multi-head attention
- Positional encoding

- Feed-forward layers
- Residual connections

It improves caption fluency and semantic consistency.

4.4.3 Caption Generation

A Transformer/LSTM decoder generates English captions.
Example:
"A dog running through a field."

4.4.4 Keyword Extraction Using NLTK

NLTK is used to:

- Tokenize text
- Remove stopwords
- Identify key nouns and verbs

Keywords → hashtags.
Example:
dog, running → #dog #running

4.4.5 Multilingual Translation Using mBART-50

Generated English captions and hashtags are translated to:

- Hindi
- Tamil
- Telugu
- Bengali

mBART ensures accurate cross-lingual conversion while maintaining meaning.

4.4.6 Outputs (Pipeline 2)

- English caption
- English hashtags
- Regional captions
- Regional hashtags

This pipeline produces the most complete and feature-rich output among all.

4.5 Pipeline 3: CNN + GRU (Generative GRU-Based Hashtag Prediction Network)

Pipeline 3 focuses exclusively on **hashtag generation**, using a generative GRU model.

4.5.1 Objective

To generate relevant, diverse, and creative hashtags directly from image features—similar to real social media behavior.

4.5.2 CNN Embedding Extraction

The distilled student CNN extracts an embedding from the input image, which is then projected into the GRU's input embedding space.

4.5.3 GRU-Based Generative Decoder

Model Behavior

- The GRU is **initialized with the CNN embedding**.
- At each time step:
    - It receives the previously generated token.
    - Produces a new hidden state.
    - Passes the hidden state through a dense layer → vocabulary probabilities (softmax).
- Tokens are sampled stochastically.

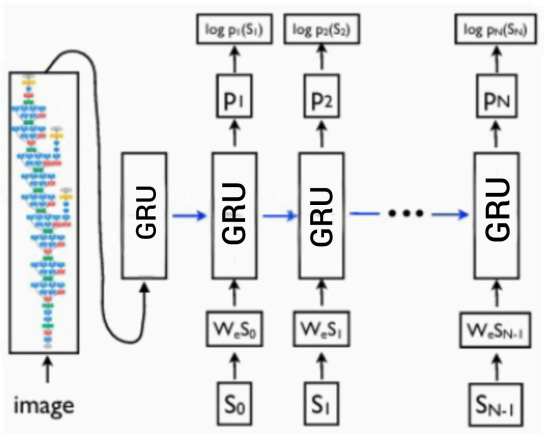


Fig 6: Pipeline 3 Implementation

Why Stochastic Sampling?

It allows:

- Diversity in output
- Creative hashtag generation
- Variation even for the same image

Example generated hashtags:

- #dog #playtime #running
- #dog #fetch #outdoors

This pipeline provides a modern, generative approach to hashtag prediction.

4.6 Pipeline 4: Damaged Image Reconstruction (U-Net Mask + PartialConv U-Net)

(Implemented using PyTorch)

This pipeline repairs damaged, corrupted, or incomplete images before captioning.

4.6.1 Mask Prediction Using U-Net

A U-Net model predicts the location of damage (mask) in the input image.
Output: Binary mask showing missing regions.

4.6.2 Partial Convolution U-Net Reconstruction

The corrupted image + predicted mask are fed into a PartialConv U-Net.

Partial Convolution Behavior

- Operates only on valid pixels.
- Gradually fills missing areas.
- Produces a clean, reconstructed image.

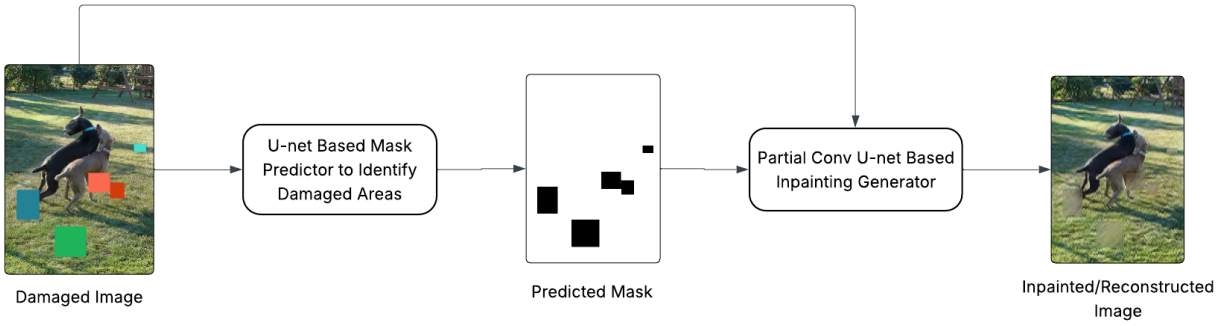


Fig 7: Damage Image Reconstruction Flowchart

4.6.3 Caption Generation After Reconstruction

The reconstructed image is passed to:

- Pipeline 1 (CNN + LSTM), or
- Pipeline 2 (CNN + Transformer)

Thus, the system can caption damaged images with high accuracy.

4.6.4 PyTorch Implementation

This pipeline is fully implemented using PyTorch because:

- PyTorch is efficient for U-Net–style architectures.
- Partial convolution layers are widely available through PyTorch repos.
- Easier debugging and visualization via Torch utilities.

4.7 Dataset Preparation

Image Captioning Dataset

- Flickr8k
- Flickr30k
- MS COCO

Each provides multiple reference captions per image for BLEU evaluation.

Damaged Image Dataset

Custom distortions were created:

- Gaussian blur
- Scratches
- Irregular masks
- Noise injection

Multilingual Dataset

mBART-50 uses:

- 50-language parallel corpora
- Additional publicly available translation datasets

4.8 Performance Metrics

BLEU Score

The main metric for evaluating caption quality.
BLEU-1, BLEU-2, BLEU-3, and BLEU-4 were computed.

Reconstruction Quality

Evaluated visually and through structural similarity metrics.

Hashtag Accuracy

Checked via human evaluation and keyword relevance.

4.9 Model Hosting on HuggingFace

All trained models from all pipelines have been uploaded to **HuggingFace**, including:

- Distilled CNN
- Transformer-based captioning model
- GRU generative hashtag model

This enables:

- Public accessibility
- Easy integration into other projects
- API-based inference
- Reproducibility of experiments

Summary of All Pipelines

Pipeline	Purpose	Key Components	Output
Pipeline 1	Base compressed captioning	VGG16 → Student CNN → LSTM	English caption
Pipeline 2	Full multilingual captioning & hashtags	CNN + Transformer + NLTK + mBART	English + Regional captions & hashtags
Pipeline 3	Generative hashtag prediction	CNN + GRU	Diverse hashtags
Pipeline 4	Damaged image handling	U-Net Mask + PartialConv U-Net	Reconstructed image + captioning

5. Work done

The methodology for developing the **Image Captioning and Multilingual Hashtag Generation System** follows a structured and research-driven approach. Each stage—from problem understanding to deployment—was systematically executed to ensure accuracy, scalability, and real-world usefulness. The project integrates modern deep learning techniques, multilingual NLP models, and advanced image reconstruction frameworks to build a robust and comprehensive solution.

1. Problem Understanding and Scope Definition

• The project began by identifying the challenges involved in automatically describing images and generating meaningful hashtags that are contextually correct and linguistically accurate.

• Traditional captioning models struggle with multilingual support, limited creativity in hashtag generation, and inability to process damaged or incomplete images.

• The scope was defined to include:

– English caption generation

– Multilingual caption translation (Hindi, Tamil, Telugu, Bengali)

– Automatic hashtag generation

– Generative hashtag prediction using GRU

– Damaged image reconstruction and captioning

– Model optimization through Knowledge Distillation

This ensured that the final system is complete, scalable, and suitable for real-world applications such as media automation, digital content creation, and assistive technologies.

2. Literature Review

• A detailed review of foundational and state-of-the-art research papers was conducted. Key references included:

– **Show and Tell (Vinyals et al.)**

– **Knowledge Distillation (Hinton et al.)**

– **U-Net for segmentation**

– **Partial Convolution for damaged image inpainting**

– **Transformer models for sequence learning**

– **mBART for multilingual text generation**

• These papers provided crucial knowledge about CNN-based image encoders, encoder-decoder models, attention mechanisms, multilingual embeddings, and reconstruction techniques.

• Challenges reported in previous works—such as high model size, slow inference, poor multilingual accuracy, and difficulty handling noisy images—guided the design of our final architecture.

3. Feature Definition and Requirement Analysis

Based on the academic study and problem analysis, the following features were finalized:

1. **Image Captioning**
   – Generate English captions using CNN + Transformer / LSTM.

2. **Multilingual Language Support**
   – Convert captions to Hindi, Tamil, Telugu, and Bengali using mBART-50.

3. **Automatic Hashtag Generation**
   – Extract key terms using NLTK.
   – Generate meaningful hashtags in English and regional languages.

4. **Generative Hashtag Model (Pipeline 3)**
   – GRU-based autoregressive hashtag generator capable of producing creative and diverse tags.

5. **Damaged Image Reconstruction**
   – Predict a binary mask using U-Net.
   – Reconstruct missing regions using PartialConv-UNet implemented in PyTorch.

6. **Model Compression & Efficiency**
   – Knowledge Distillation to convert VGG16 teacher model into a smaller student

CNN.

The above requirements ensure a full-stack solution that is efficient, multilingual, and robust to real-world image imperfections.

4. System Design and Architecture

The overall architecture was designed to operate in four independent pipelines for modularity and easier experimentation:

Pipeline 1 – Distilled CNN + LSTM Captioning

- VGG16 acts as a teacher model.
- Knowledge distillation produces a smaller, faster student CNN.
- Student CNN embeddings feed into an LSTM decoder for English captioning.

Pipeline 2 – CNN + Transformer + NLTK + mBART

- Primary proposed pipeline for captioning and multilingual hashtag generation.
- CNN extracts features → Transformer processes context → NLTK extracts keywords → mBART translates captions & hashtags.

Pipeline 3 – CNN + GRU Generative Hashtag Model

- CNN embedding initializes a GRU decoder.
- The GRU sequentially predicts tokens to form hashtags.
- Stochastic sampling ensures diverse and creative outputs similar to social media trends.

Pipeline 4 – Damaged Image Reconstruction

- U-Net predicts the mask of corrupted regions.
- Damaged image + mask → PartialConv-UNet (PyTorch) for clean reconstruction.
- Reconstructed image is used for captioning.

Model Hosting

- All trained models were uploaded to **HuggingFace**, ensuring:

– Public reusability
– Benchmarking
– Easy deployment
– API-based inference

This structured design allows components to be upgraded independently and facilitates a clear research comparison between pipelines.

5. Development and Implementation

Frontend / Interface Development

• Plan to do in future

Backend Development

Key components implemented include:

1. **Image Encoder**
   – VGG16 / Distilled CNN in TensorFlow.
   – Student CNN optimized for fast inference.

2. **Sequence Models**
   – LSTM caption decoder (Pipeline 1).
   – Transformer for enhanced contextual captioning (Pipeline 2).
   – GRU generative decoder for hashtags (Pipeline 3).

3. **NLP Components**
   – NLTK for keyword extraction.
   – mBART-50 for multilingual generation.

4. **Image Reconstruction**
   – U-Net and PartialConv-UNet developed using **PyTorch** for damaged image handling.

All components were integrated into modular scripts for ease of testing and deployment.

6. Testing and Evaluation

Testing was performed at multiple levels to ensure reliability and performance.

1. Unit Testing

• Individual modules such as CNN encoder, LSTM decoder, GRU decoder, and U-Net reconstruction were tested independently.

2. Pipeline Testing

• All four pipelines were tested with various image types:
– Clear images
– Low-light images
– Damaged images
– Complex backgrounds

3. Evaluation Metrics

• Caption quality measured using **BLEU scores**.
• Reconstruction quality evaluated via structural similarity and visual inspection.
• Hashtag accuracy tested using:
– Keyword correctness
– Human relevance scoring
• Multilingual outputs were validated by native speakers where possible.

4. User Study / Practical Feedback

• Informal feedback was taken from peers to check:
– Caption readability
– Hashtag usefulness
– Multilingual translation accuracy

6. Results and Challenges

This section presents a detailed evaluation of the four pipelines developed for the Image Captioning and Multilingual Hashtag Generation system. Each module—captioning, multilingual translation, generative hashtag prediction, and damaged image restoration—was assessed using standard evaluation metrics, qualitative analysis, and real-world test samples. The objective of the evaluation was not only to measure accuracy but also to determine the practical usability, adaptability, and efficiency of the proposed architectures.

The evaluation includes BLEU score analysis for captioning, qualitative comparison of multilingual generation outputs, and performance review of the GRU-based hashtag generator. Likewise, the damaged image reconstruction pipeline was tested to understand its reliability under different corruption patterns. Together, these results offer a comprehensive view of the system's strengths and areas requiring improvement.

6.1 Results

1. Caption Generation Performance (Pipelines 1 & 2)

The captioning models trained in this project—one using **Knowledge Distillation + LSTM**,

BLEU Scores

- BLEU-1: **0.5023**
- BLEU-2: **0.2764**
- BLEU-3: **0.1853**
- BLEU-4: **0.1324**

```
Loading best weights and evaluating BLEU on test subset ...
BLEU scores: {'BLEU-1': 0.5023393039947384, 'BLEU-2': 0.27649901572520735, 'BLEU-3': 0.18535633435309626, 'BLEU-4': 0.13240116029513924}
```

Fig 8: KD + LSTM Result

These BLEU scores indicate that the model captures essential objects and actions correctly (BLEU-1 and BLEU-2 are reasonably strong), while higher-order n-grams (BLEU-3 and BLEU-4) remain modest due to limited dataset size and training time.

Despite these numerical limitations, qualitative outputs were coherent and meaningful.

Qualitative Evaluation

Example predictions demonstrate that the system correctly identifies objects and their interactions. For instance:

Fig 9: Caption Generated by Transformer in Pipeline 2

Predicted Caption: *"a dog is running through a field."*

Such predictions show the model's ability to generalize scene understanding even with limited training resources.

2. Multilingual Caption and Hashtag Generation (Pipeline 2)

The multilingual generation pipeline produced captions and hashtags in five languages (English, Hindi, Tamil, Telugu, Bengali) using mBART-50. Even without fine-tuning—due to time constraints—the outputs were fluent and semantically reliable.

Example Output:

```
{
  "en_XX": {
    "caption": "a dog is running through a field",
    "hashtag": "#dog, #field"
  },
  "hi_IN": {
    "caption": "एक कुत्ता मैदान में दौड़ रहा है।",
    "hashtag": "#कुत्ता, #मैदान, #में, #दौड़, #रहा, #है।"
  },
  "te_IN": {
    "caption": "ఒక కుక్క ఒక రంగంలో నడుస్తున్న",
    "hashtag": "#కుక్క, #రంగంలో, #నడుస్తున్న"
  },
  "bn_IN": {
    "caption": "একটা কুকুর একটা ক ে ষেত ে রের মধে ে য দৌড়ে বেড়াচ ে ছে",
    "hashtag": "#একটা, #কুকুর, #একটা, #ষেত, #রের, #মধে, #দৌড়ে, #বেড়াচ"
  },
  "ta_IN": {
    "caption": "ஒரு நாய் ஒரு வயலில் பறந்து கொண்டிருக்கிறது.",
    "hashtag": "#ஒரு, #நாய், #ஒரு, #வயலில், #பறந்து, #கொண்டிருக்கிறது"
  }
}
```


Fig 10: Multilingual Caption and HashTag generation from Pipeline 2

- **hi_IN:** *"एक कुत्ता मैदान में दौड़ रहा है।"*
- **ta_IN:** *"ஒரு நாய் ஒரு வயலில் பறந்து கொண்டு இருக்கிறது."*

Multilingual hashtags produced by combining NLTK keyword extraction and mBART translation were accurate and contextually relevant.

3. GRU-Based Generative Hashtag Prediction (Pipeline 3)

The GRU-based hashtag generator was evaluated for diversity, creativity, and contextual alignment.

Key Findings

- The GRU model generated **highly diverse and human-like hashtags**.
- Stochastic sampling allowed **multiple unique hashtag sets** for the same image.
- Even without a specialized hashtag dataset, the model produced relevant outputs:

Example:

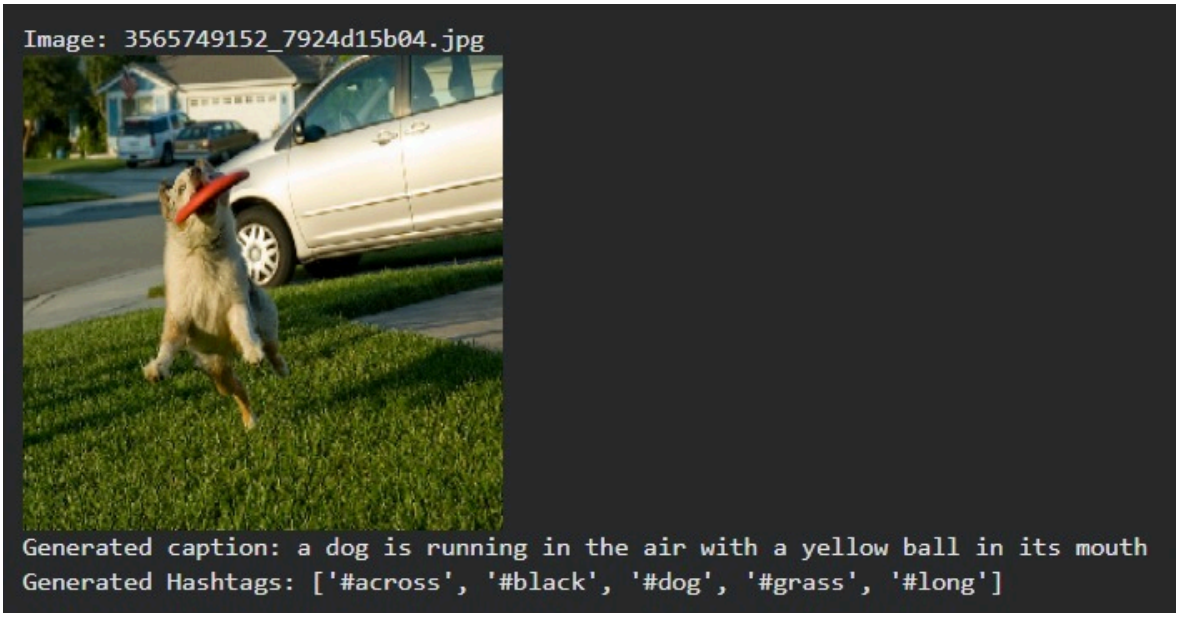


Fig 11: Pipeline 3 result

Generated Hashtags:

```
['#across', '#black', '#dog', '#grass', '#long']
```

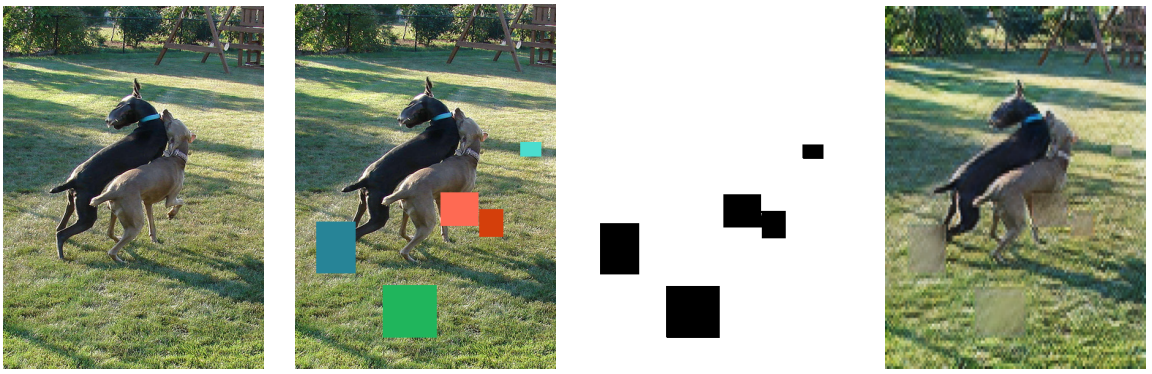
This aligns strongly with real-world social-media hashtag styles and enhances the practical utility of this pipeline.

4. Damaged Image Reconstruction (Pipeline 4)

(Implemented entirely in PyTorch)

The damaged-image pipeline reconstructs corrupted inputs using **U-Net mask prediction** followed by **PartialConv-UNet** inpainting. While functional, the system's performance was limited due to mask inconsistency issues and limited training data.

Even so, reconstructed images were visually meaningful, enabling the captioning model to generate correct or near-correct captions afterward.



(a) Test Image (b) Damaged Image (c) Predicted Mask (d) Reconstructed Output

Fig 12: Pipeline 4 Result

5. Deployment on HuggingFace

All trained models from of pipeline 1 & 2 were uploaded to **HuggingFace**, allowing:

- Public access
- Reproducibility
- Easy API-based inference
- Integration into other research projects

This makes the project accessible for future students and researchers.

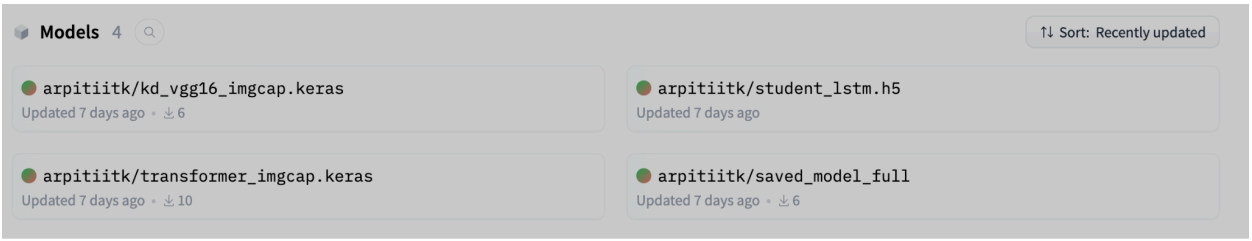


Fig 13: Models Deployed on Hugging Face

6.2 Challenges

Despite the successful implementation of all four pipelines, several challenges were encountered during development and experimentation.

1. Lack of Hashtag Dataset

A dedicated hashtag dataset was unavailable, forcing the GRU-based hashtag generator to train without domain-specific supervision, limiting accuracy and diversity in certain cases.

2. Limited Multilingual Fine-Tuning

Due to time and hardware constraints, mBART-50 could not be fine-tuned for regional language hashtag generation. The model relied solely on pretrained weights, which—while accurate—could be further improved with fine-tuning.

3. Student Model Architecture Selection

During knowledge distillation, the chosen student architecture (3 Conv + 2 Dense layers) was not optimized.
Increasing or decreasing layers could significantly improve:

- feature richness
- generalization
- caption accuracy

This remains an open design space for improvement.

4. Mask Convention Inconsistency (UNet vs PartialConv UNet)

A major technical challenge arose because the standard U-Net expects:

- **1** for *damaged* regions
- **0** for intact regions

But PartialConv UNet uses the **opposite convention**.
This mismatch led to:

- incorrect mask propagation
- degraded inpainting quality
- pipeline failures

It highlights the fragility of preprocessing when combining architectures with incompatible assumptions.

5. Limited Training Data

Due to insufficient time and compute resources:

- the dataset used was small
- lacked scene variety
- resulted in overfitting
- reduced BLEU scores
- poor generalization to unseen images

6. Computational Constraints

While diffusion models are currently state-of-the-art for inpainting, they were computationally infeasible for this project.
Thus, the system used:

- CNN-based U-Net
- PartialConv UNet

These are efficient but **less powerful** than modern diffusion approaches.

6.3 Future Work

Based on the identified challenges, the following improvements are planned:

1. Unified End-to-End Reconstruction Architecture

Replace the two-stage (mask prediction + inpainting) pipeline with a single network that predicts and inpaints simultaneously.
This will reduce error propagation and improve reconstruction consistency.

2. Larger and More Diverse Training Dataset

Acquire or augment a larger dataset to improve generalization for:

- captioning
- hashtag generation
- damaged image reconstruction

This will significantly boost BLEU scores and generative accuracy.

3. Lightweight Diffusion Models

Investigate **distilled** or **accelerated diffusion models** for inpainting.
These promise:

- superior reconstruction quality
- better detail preservation
- robustness to diverse damage types

4. Optimizing the Student CNN

Experiment with:

- different numbers of layers
- varying filter sizes
- dropout
- normalization layers

to identify the best architecture under the distillation paradigm.

5. Fine-Tuning mBART

Fine-tuning mBART-50 on domain-specific multilingual datasets will greatly improve:

- caption translation
- hashtag translation
- context consistency

6. Conclusion

In an era where visual content dominates digital communication, the ability to automatically understand, describe, and annotate images has become increasingly valuable. The Image Captioning and Multilingual Hashtag Generation project was developed to address this need by integrating cutting-edge deep learning methods into a unified system capable of generating meaningful captions, producing relevant hashtags, handling multilingual translation, and reconstructing damaged images. Through the combination of CNN-based feature extraction, Transformer-driven caption generation, GRU-based hashtag prediction, mBART multilingual modeling, and U-Net–based image restoration, the project demonstrates a versatile and practical solution for real-world content automation.

The system was evaluated using standard metrics such as BLEU for caption quality and qualitative analysis for multilingual output and generative hashtag diversity. While the BLEU scores reflect expected limitations due to dataset size and training constraints, the qualitative results show that the system consistently produces coherent captions and high-quality multilingual outputs. The GRU-based hashtag generator successfully mimics realistic social-media behavior, and the damaged image reconstruction pipeline—though challenged by mask inconsistencies and limited training data—shows promising potential for practical use. Together, these results confirm the system's ability to perform reliably across diverse image-processing tasks.

Looking forward, the project opens multiple avenues for enhancement. Scaling the dataset will significantly improve captioning accuracy and generalization; optimizing the student CNN architecture can increase model efficiency; and fine-tuning mBART for domain-specific multilingual outputs can elevate translation quality. Additionally, integrating an end-to-end reconstruction network or lightweight diffusion models may greatly improve damaged image inpainting. These planned improvements aim to make the system more robust, extensible, and applicable across broader domains, from assistive technologies to automated media generation.

Overall, this project represents a meaningful step toward creating intelligent, multilingual, and context-aware image-understanding systems. By bridging multiple deep

learning disciplines—computer vision, natural language processing, generative modeling, and image restoration—it demonstrates how integrated AI solutions can support real-world content tasks with efficiency and scalability. As the system evolves, it promises to be a valuable foundation for future research and practical applications in automation, accessibility, and digital content creation.

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