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INTERDISCIPLINARY DOCTORAL SCHOOL

Fake News Detection through Multimodal Approaches: Machine Learning Applications

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Discipline: Information and Communication Technology

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Content

Introduction

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1. Motivation

- A challenge to the society as a compelling issue, rapid expansion and cross-area outturn
- Detection approaches have become a major alternative to manual fact-checking, attract significant attention
- A huge research gap in multi-modal fake news detection
- Models based on non-generalized dataset, various dataset limitations, narrow content, biased
- Average accuracy of the existing solutions around 75%
- ML approaches that rely on sole underlying premise of latent patterns
- Major limitation on the efficiency of the detection
- Little to no research focuses on early detection effectiveness when the required data is usually insufficient at this stage – if the approach cannot effectively detect fake news shortly, it will have marginal usage in the real world, despite result in experimental conditions

2. Research Aims

1. Address Limitations of Unimodal Approaches by exploring the limitations of existing unimodal solutions and utilizing the complementary strengths of multimodal data.
2. Integrate Dynamic Fusion Techniques based on a dynamic fusion framework where the modality adaptively contributes to detection
3. Utilize Graph Theory for Network Analysis through Graph Convolutional Networks to understand dissemination patterns
4. Propose a Comprehensive Multimodal Detection model–As the ultimate objective of this work, the proposal of a model that aims to tackle fake news across many platforms and formats by merging various models together.

3. Research Goals and Hypothesis

Hypothesis: The integration of multimodal techniques, including text, image, and graph-based data, enhances fake news detection by capturing complex patterns that single-modality approaches cannot address. The use of dynamic weighting in multimodal models optimises detection performance by adjusting the contribution of each modality based on confidence levels.

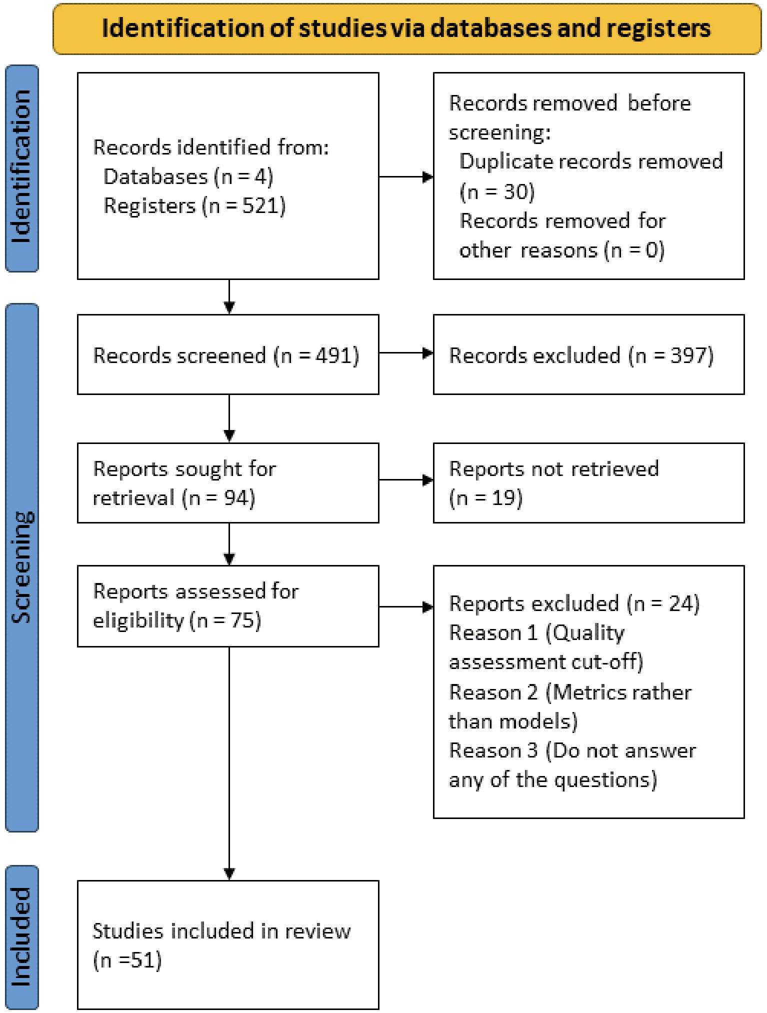
RG1: Investigate the characteristics of the current body of literature on fake news and disinformation detection

RG2: Explore graph theory and its implementations in the fake news spreading through tweet networks and patterns

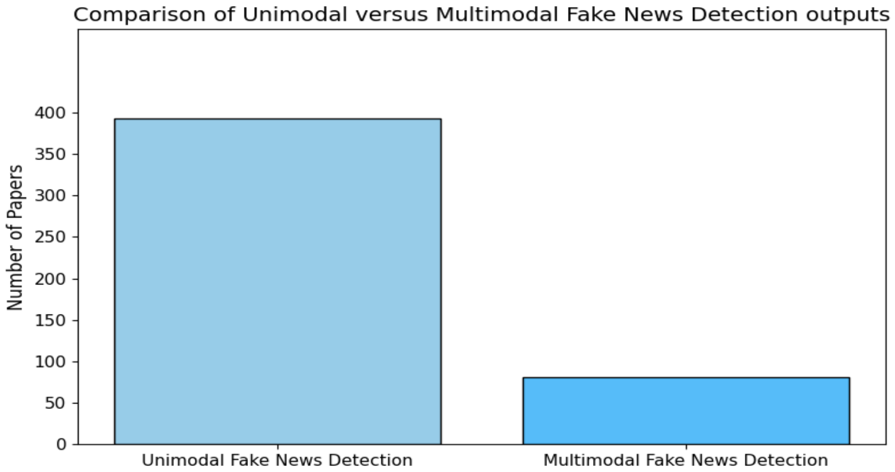
RG3: Integration of a multi-module system as a new approach to fake news detection across different content types (articles, tweets, and visual content) employing various machine learning models customised for specific problems, including ensemble approaches for textual and visual content classification.

4. Motivation undertaking research on the basis of SLR and the theoretical background

1. Which models and approaches are used in multimodal fake news detection?
2. Which machine learning techniques and approaches are effective in detecting fake news propagation patterns on social media platforms?
3. What are the most effective machine learning models in fake news detection using small training data?
4. What is the most commonly used training dataset for fake news detection models, and what are the main challenges regarding datasets?
5. What are the approaches to detecting visual content fake news?
6. Biggest challenges faced in multimodal fake news detection using machine learning?



4. Motivation undertaking research on the basis of SLR and the theoretical background



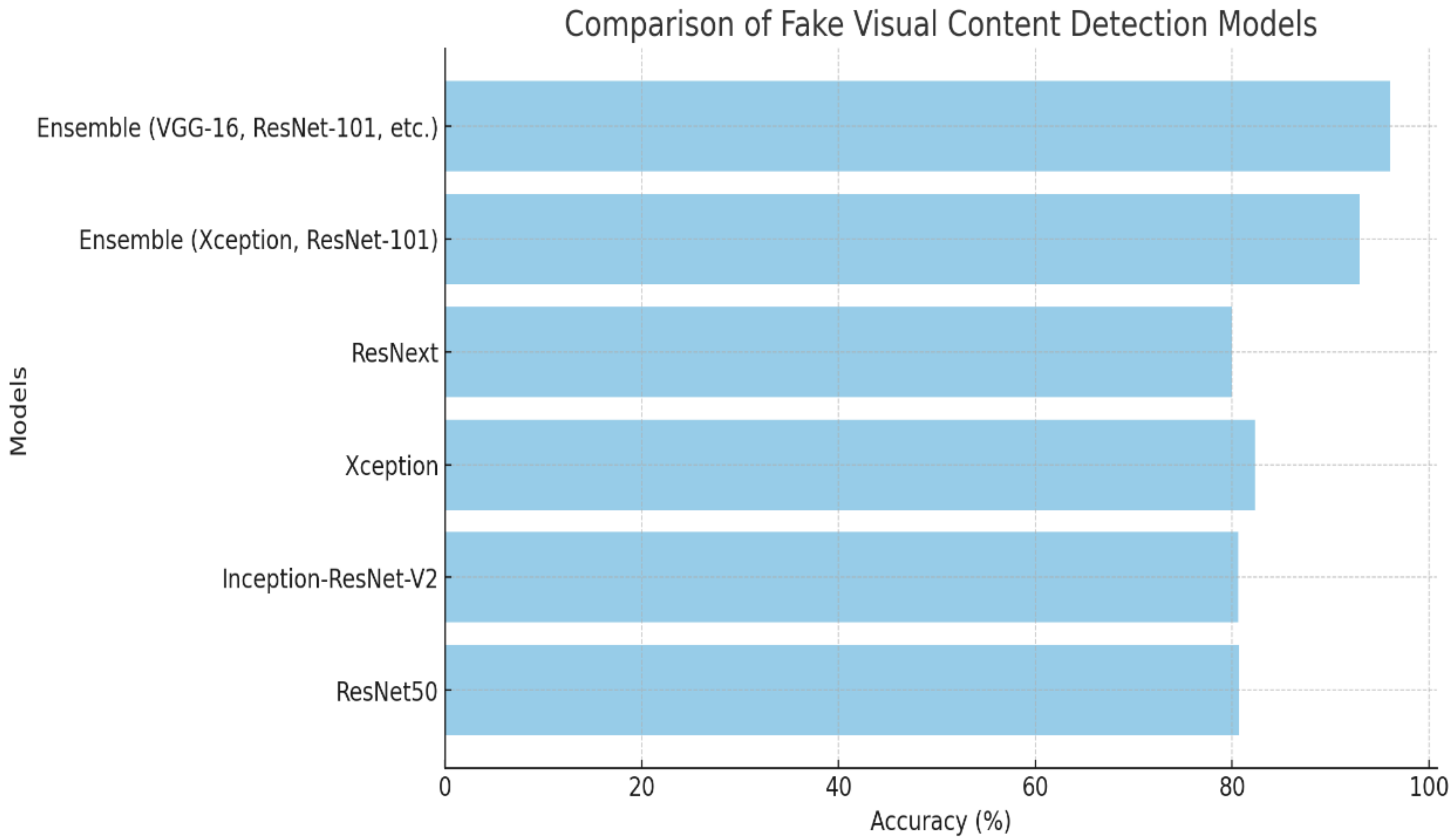
Article ref.	Methods proposed
[82]	Roberta and pretrained ResNet50
[89]	Multimodal Variational Autoencoder, using RNN, EANN, VQA, Neural Talk, VGG-19, textual- in Bi-LSTM
[126]	DNN, CNN, VGG 16, BI-LTSM word2vec
[174]	BERT to learn text features, VGG-19 pre-trained for image
[176]	Knowledge Augmented Transformer, CNN, BERT, VGG-19
[193]	CNN an VGG-19
[204]	BDANN, a BERT-based domain adaptation neural network

Article	Method used
[21]	CNN an VGG-19
[26]	BERT to learn text features, VGG-19 pre-trained for image
[22]	BDANN, a BERT-based domain adaptation neural network
[47]	DNN, CNN, VGG 16, BI-LTSM word2vec
[83]	Roberta and pretrained ResNet50
[58]	Knowledge Augmented Transformer, CNN, BERT, VGG-19
[63]	Multimodal Variational Autoencoder, RNN, EANN, VQA, Neural Talk,

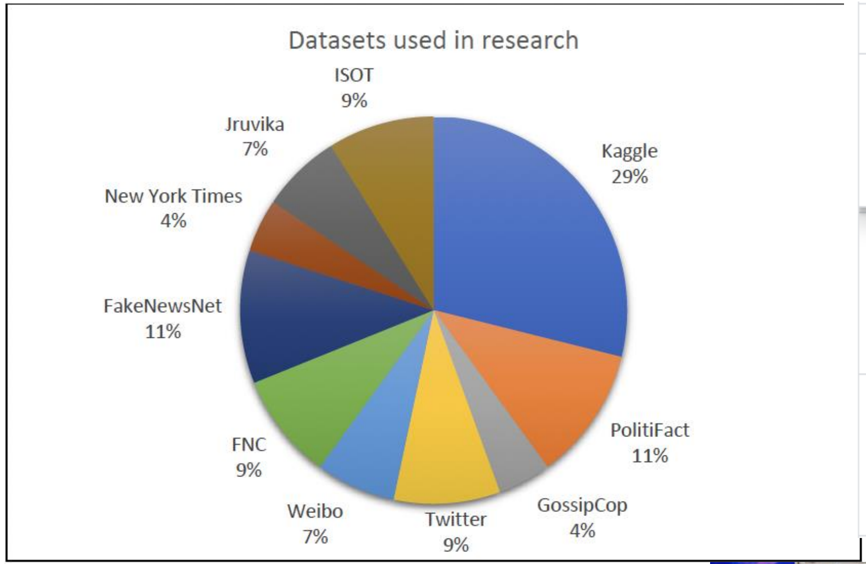
4. Comparison on some of the exiting solutions

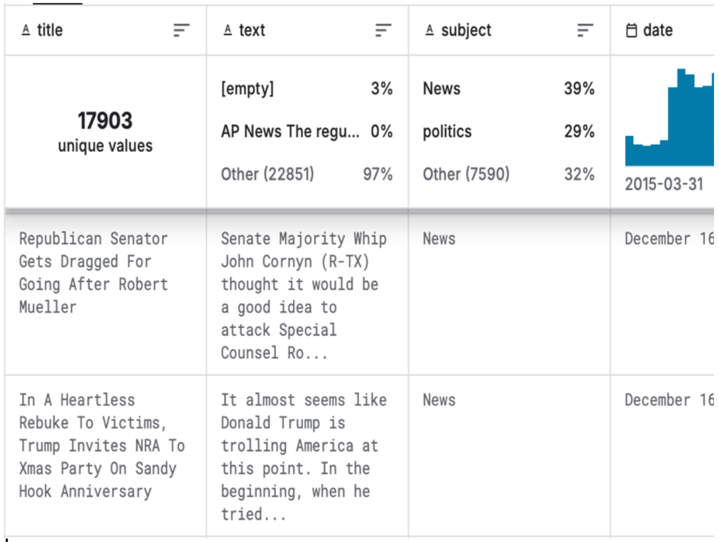
Modality	Models	Politifact	Gossipcop
Text	SVM	0.58	0.497
	Logistic Regression	0.642	0.648
	Naive Bayes	0.617	0.624
	CNN	0.629	0.723
	SAF (Social Article Fusion)	0.691	0.689
	XLNet + dense layer	**0.74**	**0.836**
	XLNet+ CNN	0.721	0.84
	XLNet + LSTM	0.721	0.807
Image	VGG19	0.654	0.80
Multimodal (Text+Image)	EANN	0.74	0.86
	MVAE	0.673	0.775
	SpotFake	0.721	0.807
	SpotFake+ (XLNet + dense + VGG19)	**0.846**	**0.856**

4. Comparison on some of the exiting solutions



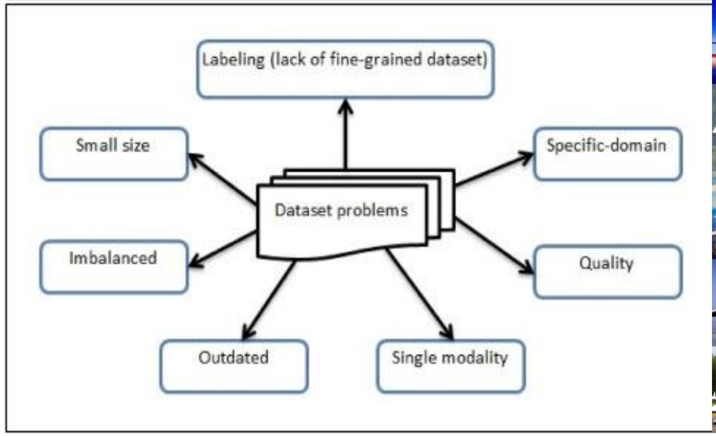
5. Datasets

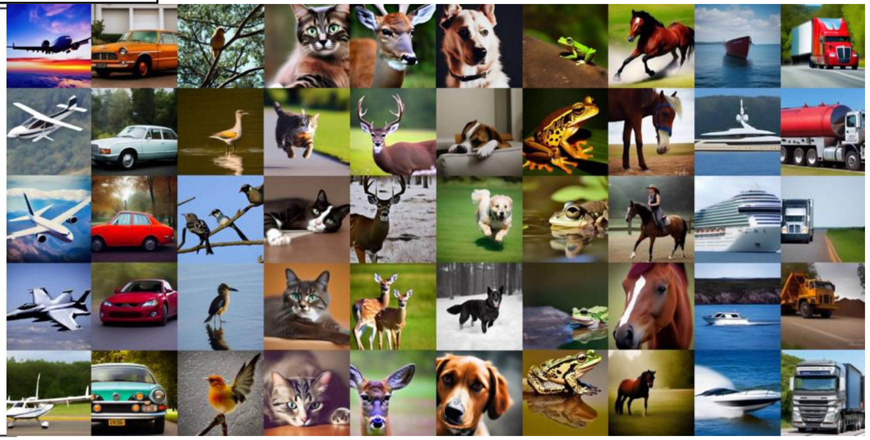




title	text	subject	date
17903 unique values	[empty] 3% AP News The regu... 0% Other (22851) 97%	News 39% politics 29% Other (7590) 32%	2015-03-31
Republican Senator Gets Dragged For Going After Robert Mueller	Senate Majority Whip John Cornyn (R-TX) thought it would be a good idea to attack Special Counsel Ro...	News	December 16
In A Heartless Rebuke To Victims, Trump Invites NRA To Xmas Party On Sandy Hook Anniversary	It almost seems like Donald Trump is trolling America at this point. In the beginning, when he tried...	News	December 16

No. Article	Methods	Datasets	Results
[87]	EfficientNetB4 XceptionNet	FF++, DFDC	90%-98%
[37]	VGG-16 + VGG-19 + ResNet-101 + InceptionV3 + SqueezeNet	MediaEval2015	97%
[160]	ResNet + Xception	DFDC	80%,78%,93%
[18]	ResNet + DenseNet	FF++	63%
[30]	EfficientNetB4	FF++, DFDC	83.8%
[39]	EfficientNetV2-M	ForgeryNet	80.1%
[92]	LBP-Net	ForgeryNet	80.1%
[93]	SiamNet (InceptioNetV3)	FF++, Celeb-DF, DFD, DFDC, DF	89%
[131]	ResNet-152,EfficientNetB0 DenseNet-12, VGG16	MobiDeep-DFD 9	98%





Label	Fake	Real	Fake	Real	Fake	Real
Vocabulary Size (words)	29,571	25,286	40,897	124,243	109,006	124,243
Avg. number of characters per item	148	219	223	216	446	216
Avg. number of words per item	27	37	38	36	81	36
Avg. number of stop-words per item	9	11	13	11	27	11

6. Methods

- Dataset with cross-area content; namely Kaggle FCN, NYT, Jurawika, FAN-21, LIAR, ISOT, FakeEdit and ImageNet, MediaEval, CIFAKE
- Pre-processing of the data: nltk black list, semantic load, stemming, tokenization, normalisation algos
- Text content features, propagation features, image features, user/publisher features
- Feature extraction, classification and ensembling methods employed in the textual model
- ResNet, Inception, DesNet, Xception and convolutions layers for the visual model alongside text processing
- Integration of models and layers to the final system, with the use of fusion/softmax

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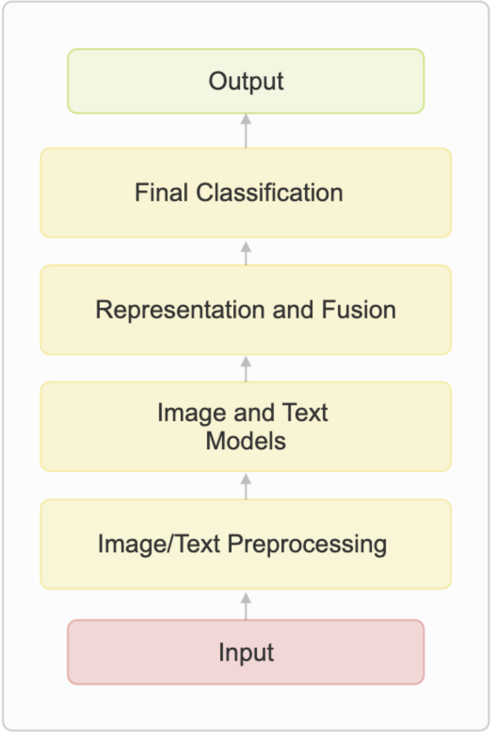
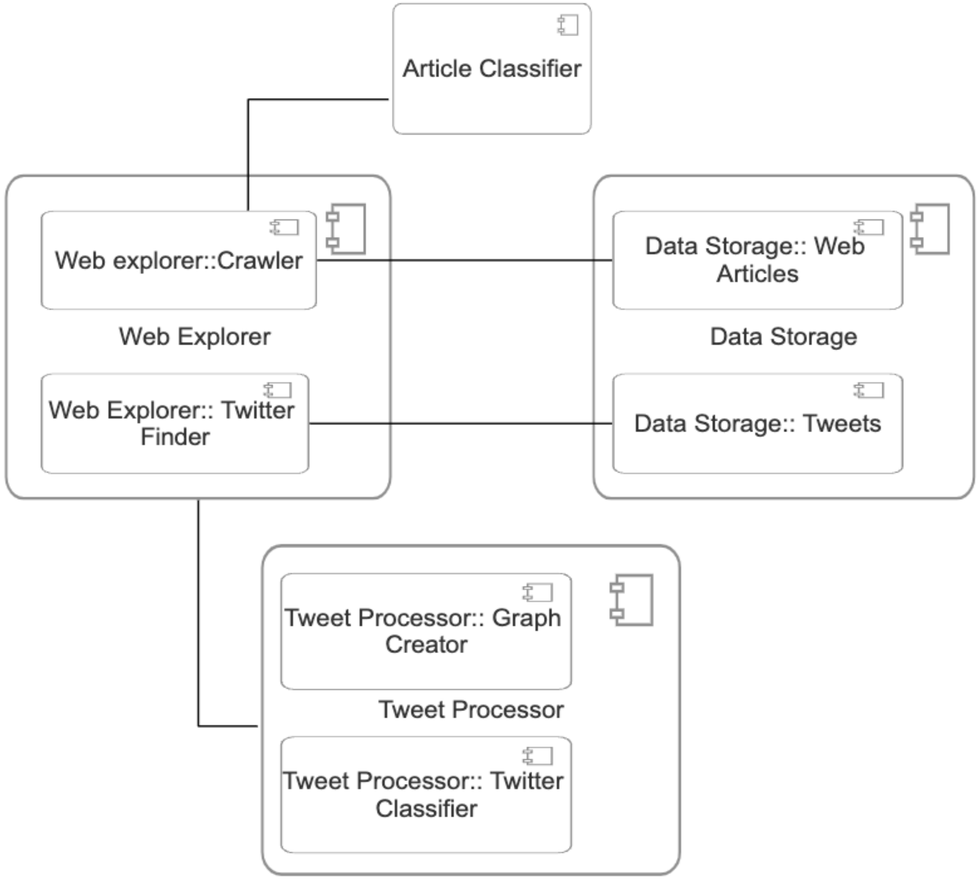
Framework overview–methodological framework



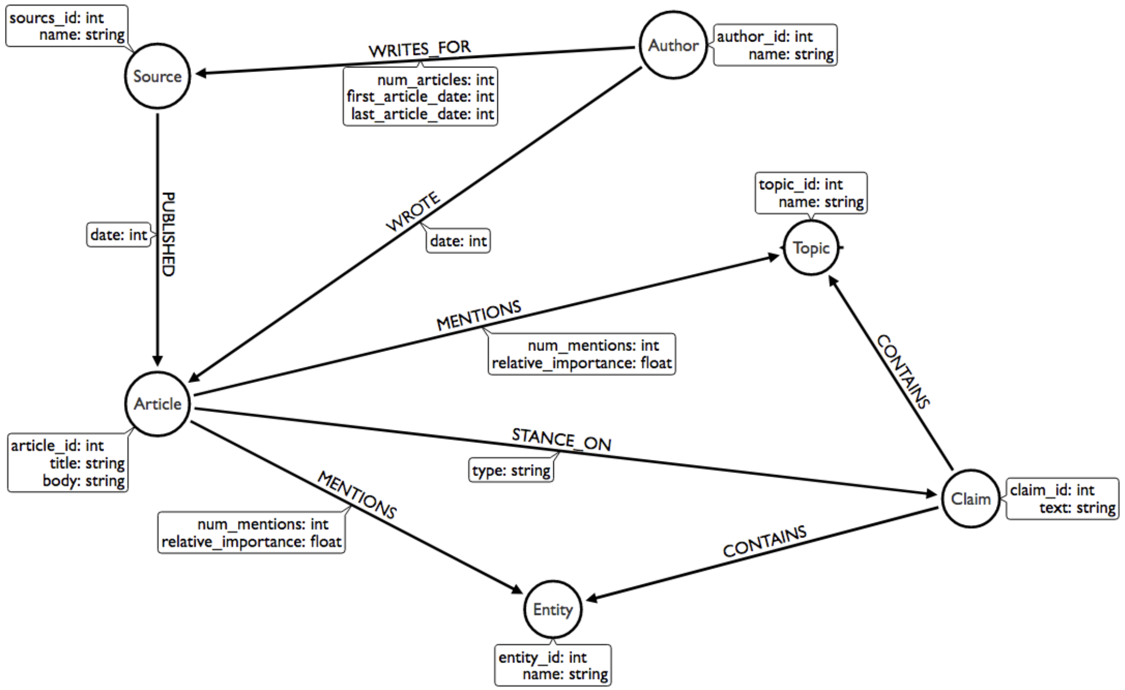
Overview of the given approach featuring basic components corresponding to the multimodal classification task



Initial components of the textual module of the solution

Framework overview -GCN model

Feature	Article Labels	Tweet Labels
Primary Label	Label (0: Real, 1: Fake)	Label (0: Real, 1: Fake)
Identifier	article_id ,	tweet_id, source_tweet_id
Text Content	Title, Content	Text
Author/Source	Author	user_id, user_screen_name
Date/Time	Date	Timestamp (in the tweet metadata)
User Interaction	-	favorite_count, retweet_count, retweeted
User Metadata	-	user_followers_count, user_description, id_source_tweet
Source URL	article_url	source



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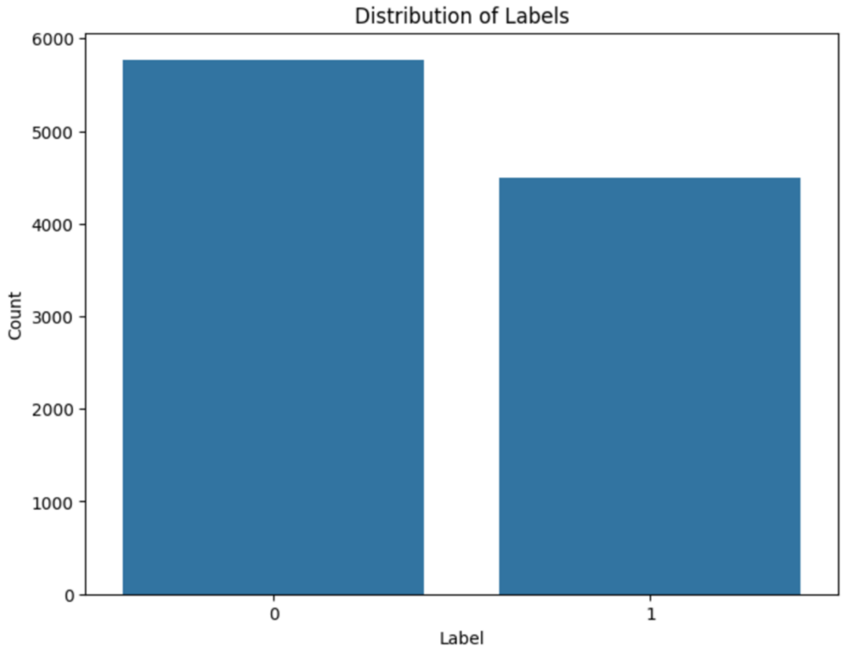
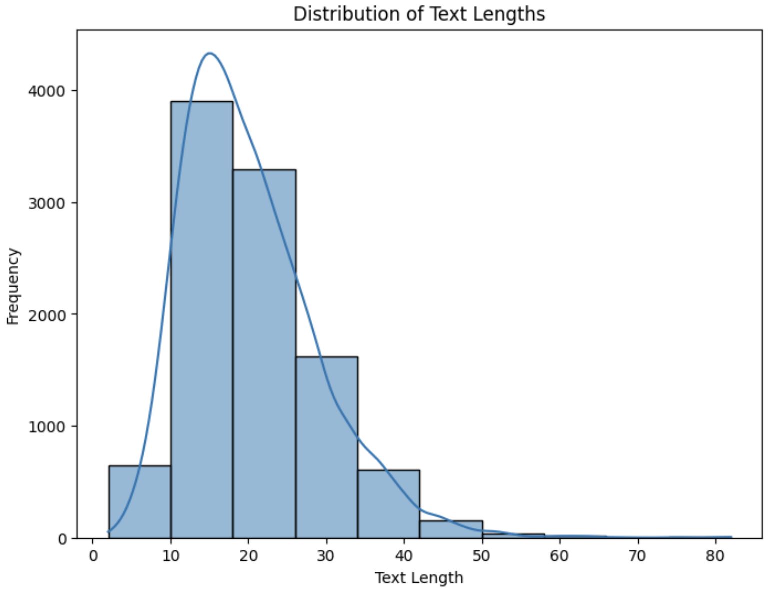
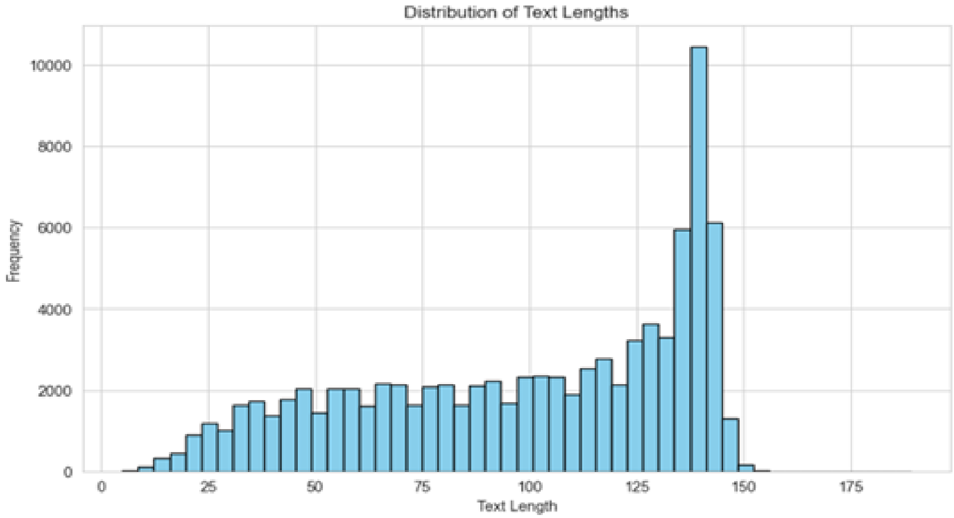
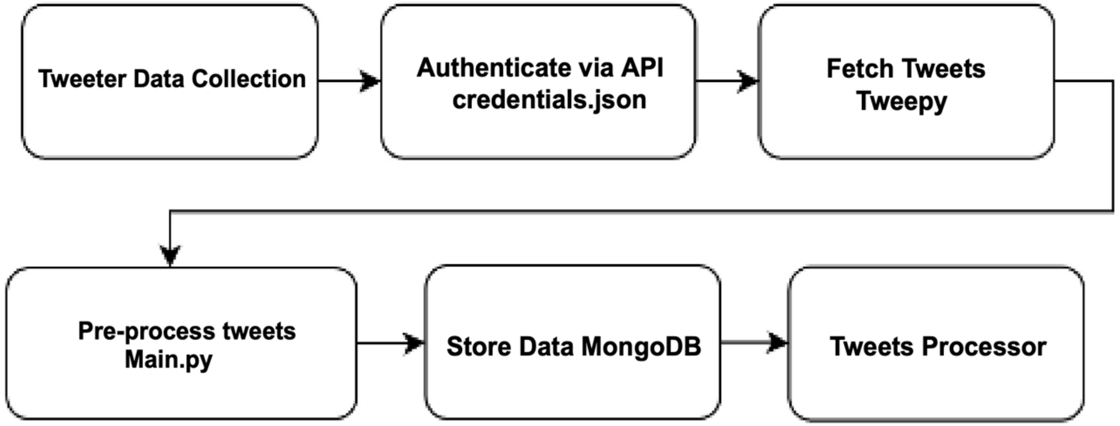
Data Preprocessing – Textual Component







Practical Implementation–GCN



Algorithm 6.1 Tweet Processing Workflow

```
Start
Execute script
Perform authorization
if Authorization fails then
    Terminate process
    End
else
    Fetch entries
    Send entries for classification
    Send entries to the Tweet Processor component
    Receive classified entries
    Send data as JSON to DataStorage:Tweets component
    End
end if
```

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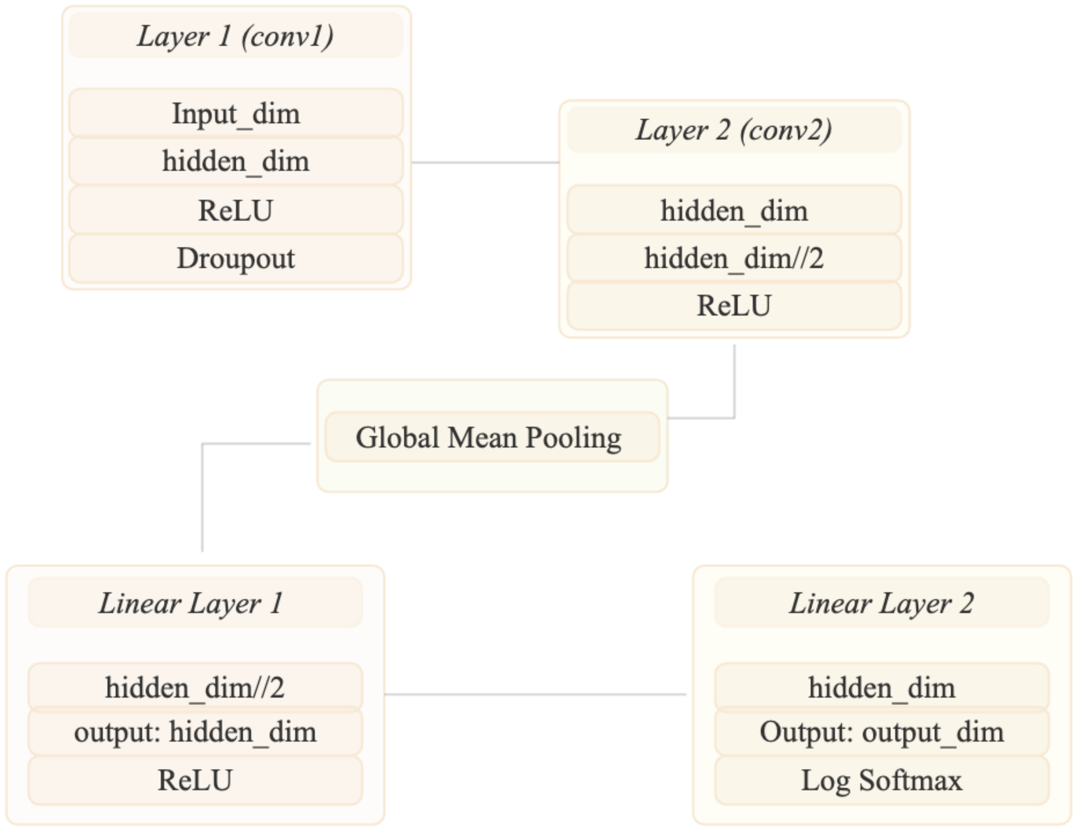
Practical Implementation–GCN

Attribute	Description
`label`	Indicates whether the tweet is fake or not.
`tweet_id`	unique identifier for the tweet.
`text`	content of the tweet.
`favorite_count`	number of reactions (likes) the tweet has received.
`source`	source or link to the tweet.
`retweeted`	Indicates whether the tweet has been retweeted.
`retweet_count`	number of retweets the tweet has received.
`user_id`	unique identifier for the user who posted the tweet.
`user_screen_name`	username of the user who posted the tweet.
`user_followers_count`	number of followers the user has.
`user_description`	description provided by the user in their profile.
`is_source_tweet`	Indicates whether the tweet is the source tweet.
`source_tweet_id`	ID of the source tweet. If the tweet is the source, this is the same as `tweet_id`.



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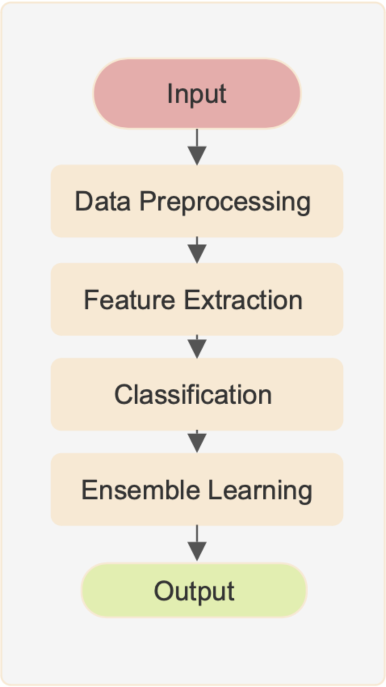
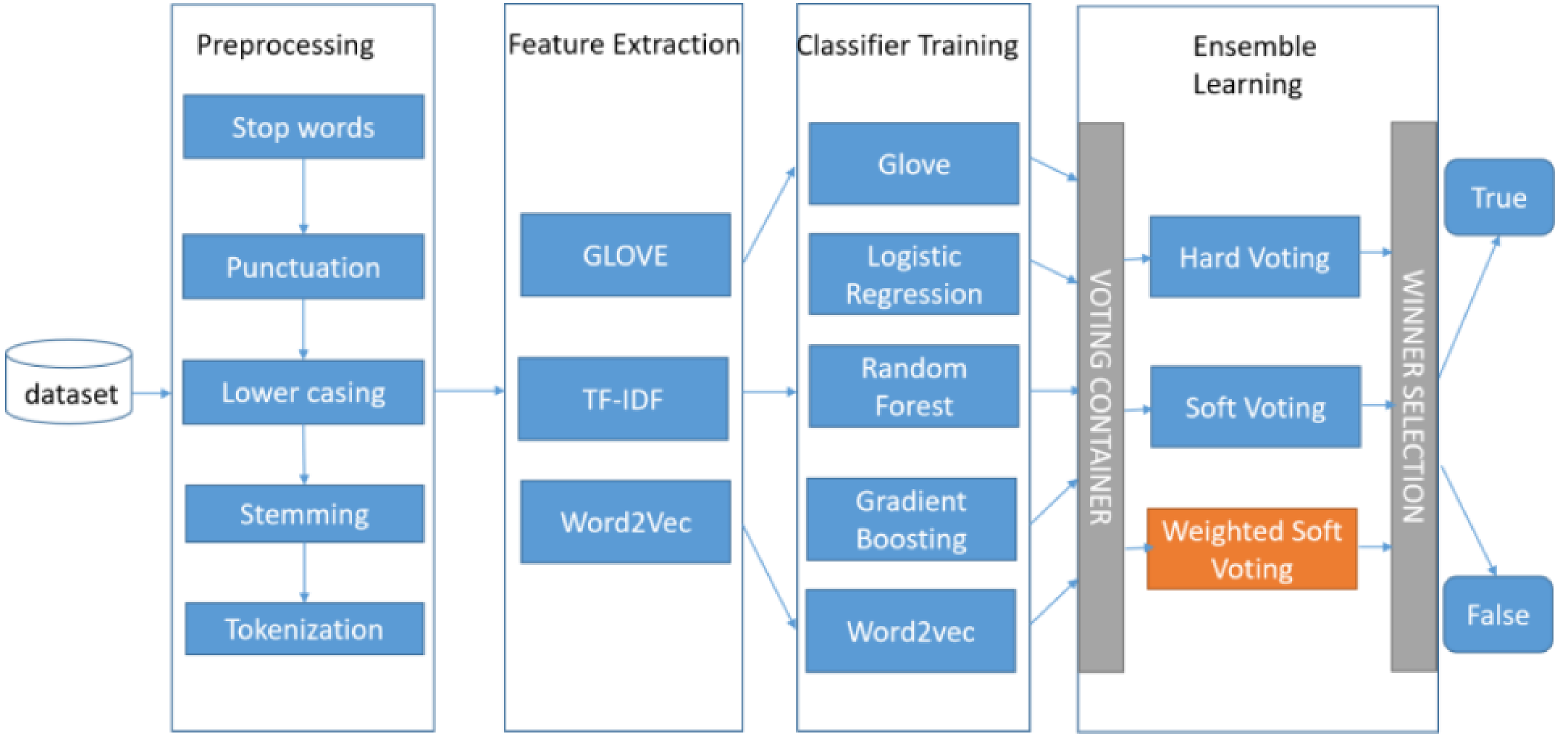
Framework overview–Textual Model





Framework Overview- Textual Model

Ensemble Learning based Fake News Detector – Textual model

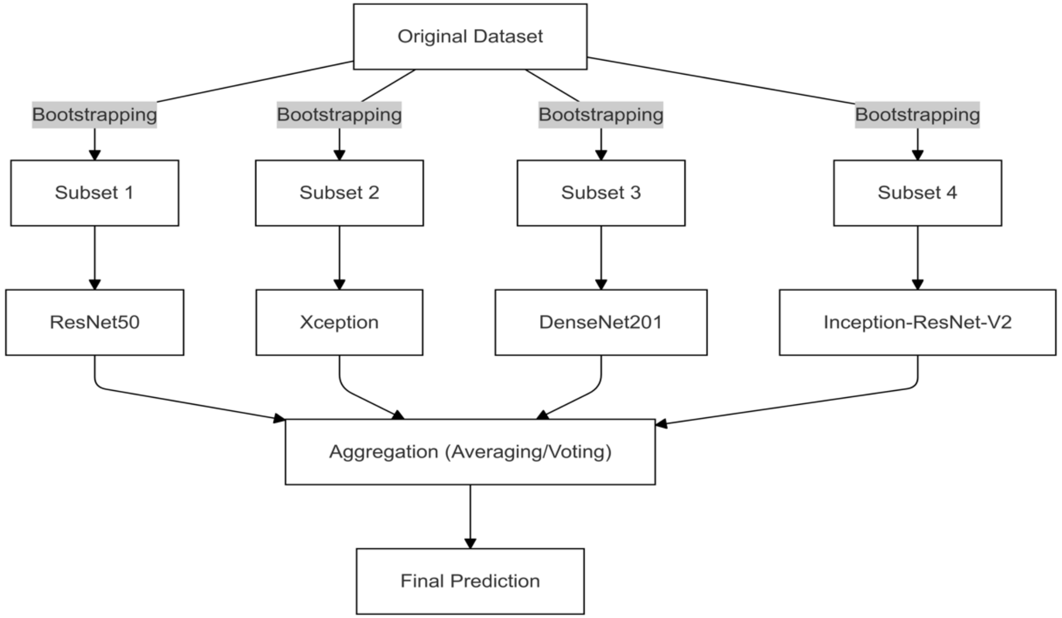
```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 300, 200)          2000000
_________________________________________________________________
lstm (LSTM)                  (None, 300, 128)          168448
_________________________________________________________________
lstm_1 (LSTM)                (None, 64)                49408
_________________________________________________________________
dense (Dense)                (None, 32)                2080
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 33
=================================================================
Total params: 2,219,969
Trainable params: 219,969
Non-trainable params: 2,000,000
_________________________________________________________________
```

Sample No	Weight	RF	GB	LR	GL	W2V	Sums
0	0	0.95	0.96	0.97	0.98	0.99	2.93
	1	0.05	0.04	0.03	0.02	0.01	0.07
1	0	0.93	0.97	0.94	0.99	0.98	2.918
	1	0.07	0.03	0.06	0.01	0.02	0.082
2	0	0.91	0.56	0.03	0.95	0.99	2.876
	1	0.09	0.44	0.97	0.05	0.01	0.124

Sample No		RF	GB	LR	GL	W2V	Sums
0	Weight	1	2	3	4	5	
	0	0.95	0.96	0.97	0.98	0.99	2.93
	1	0.05	0.04	0.03	0.02	0.01	0.07
1	Weight	1	2	3	4	5	
	0	0.93	0.97	0.94	0.99	0.98	2.918
	1	0.07	0.03	0.06	0.01	0.02	0.082
2	Weight	1	2	3	4	5	
	0	0.91	0.56	0.03	0.95	0.99	2.876
	1	0.09	0.44	0.97	0.05	0.01	0.124

Framework overview-Visual model

- The visual component
- Comparison of fake images and real-news images through a CNN model at the:
  - *physical level*- the fake-news images might be of low quality, which can be clearly reflected in the frequency domain
  - *semantic level*- images also exhibit some distinct characteristics in the pixel domain (spatial domain)



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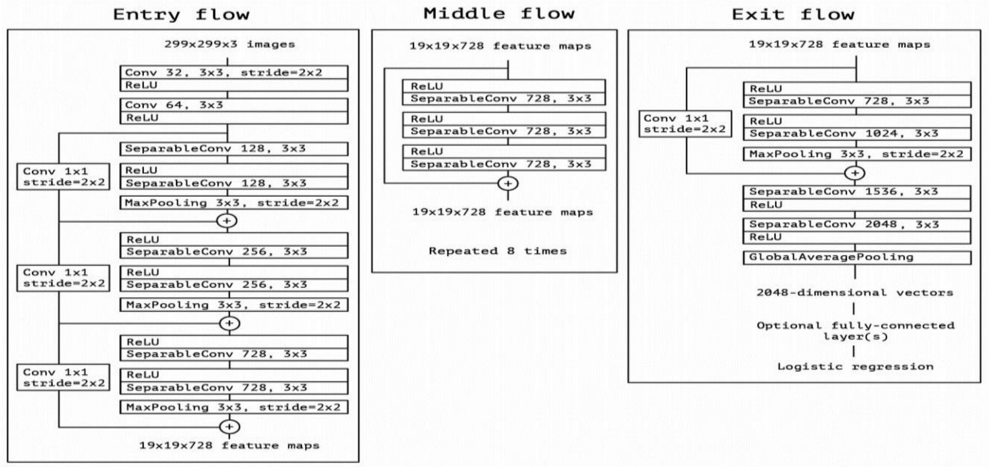
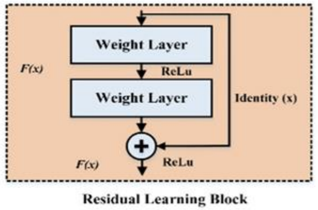
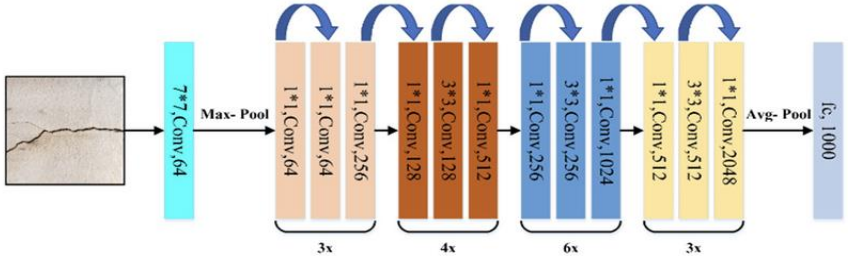
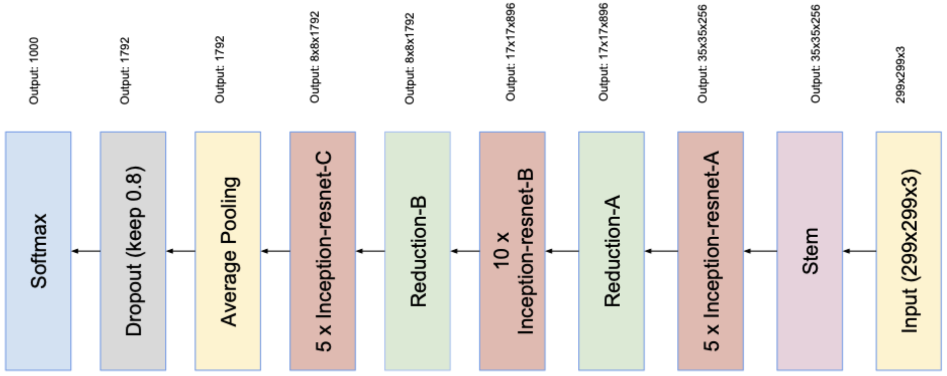
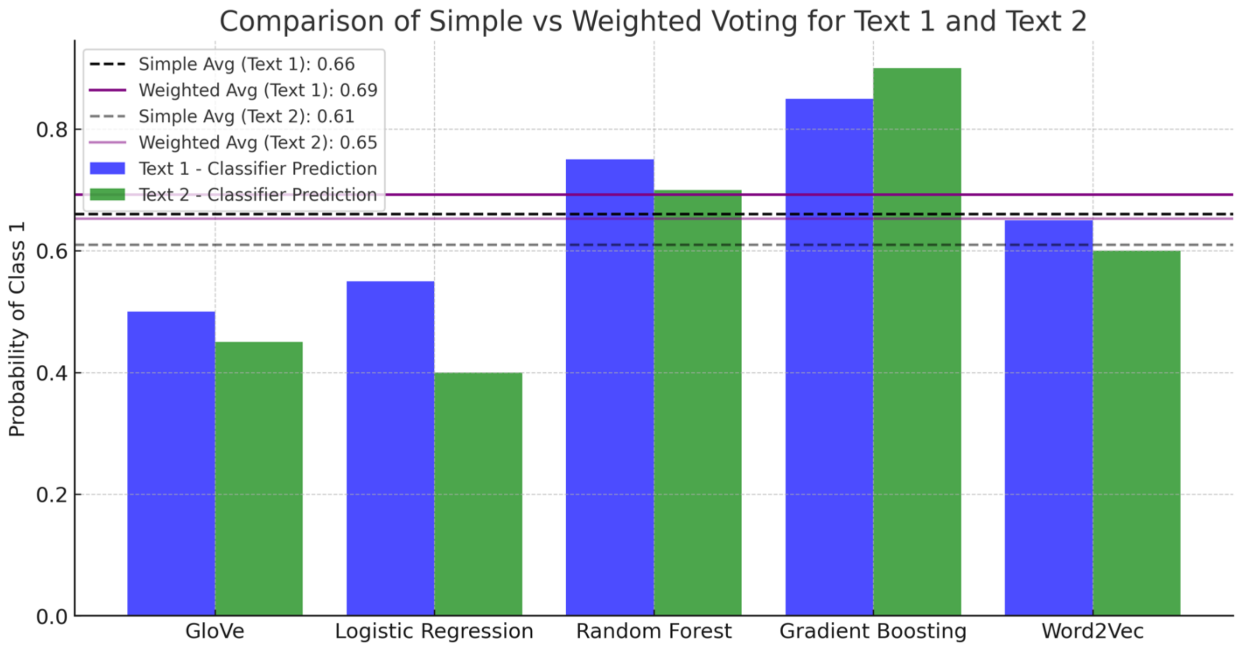
Framework overview–Visual Model











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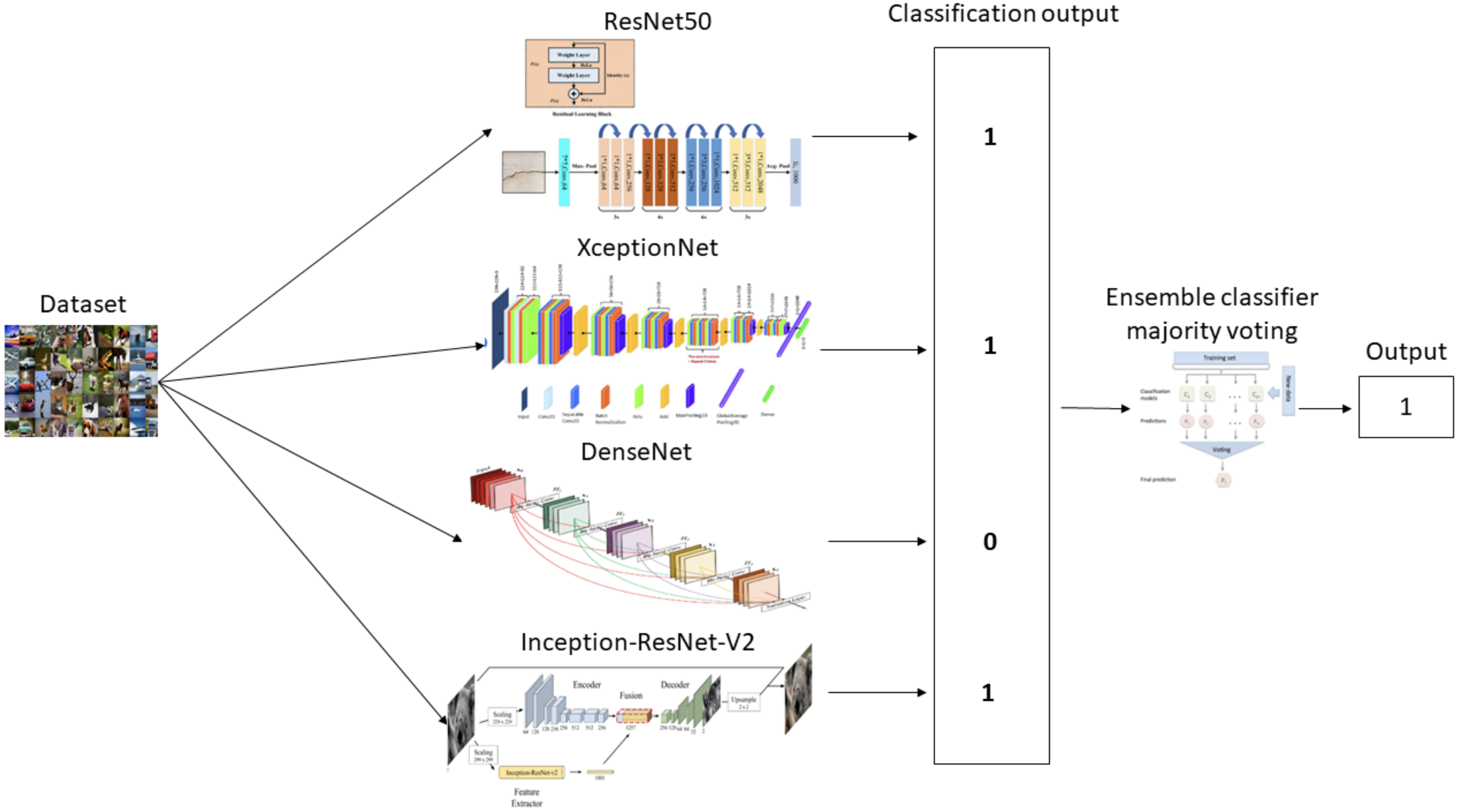
Framework overview–Visual Model

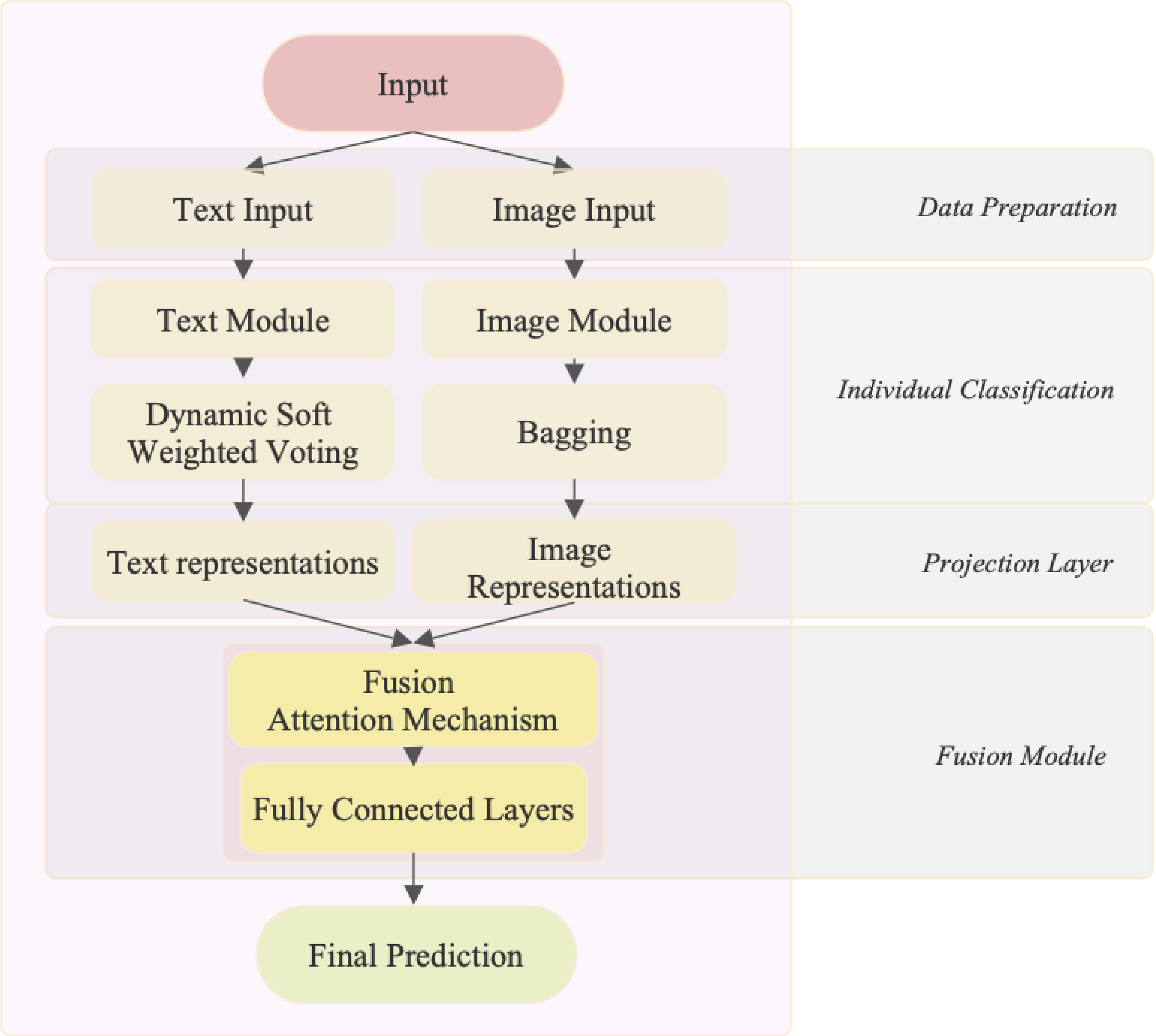
Model	Optimizer	Learning Rate	Batch Size
Xception	SGD	0.00001	32
ResNet50	RMSProp	0.0005	32
DenseNet 201	Adam	0.0001	32
Inception-ResNet-V2	Adam	0.0001	32



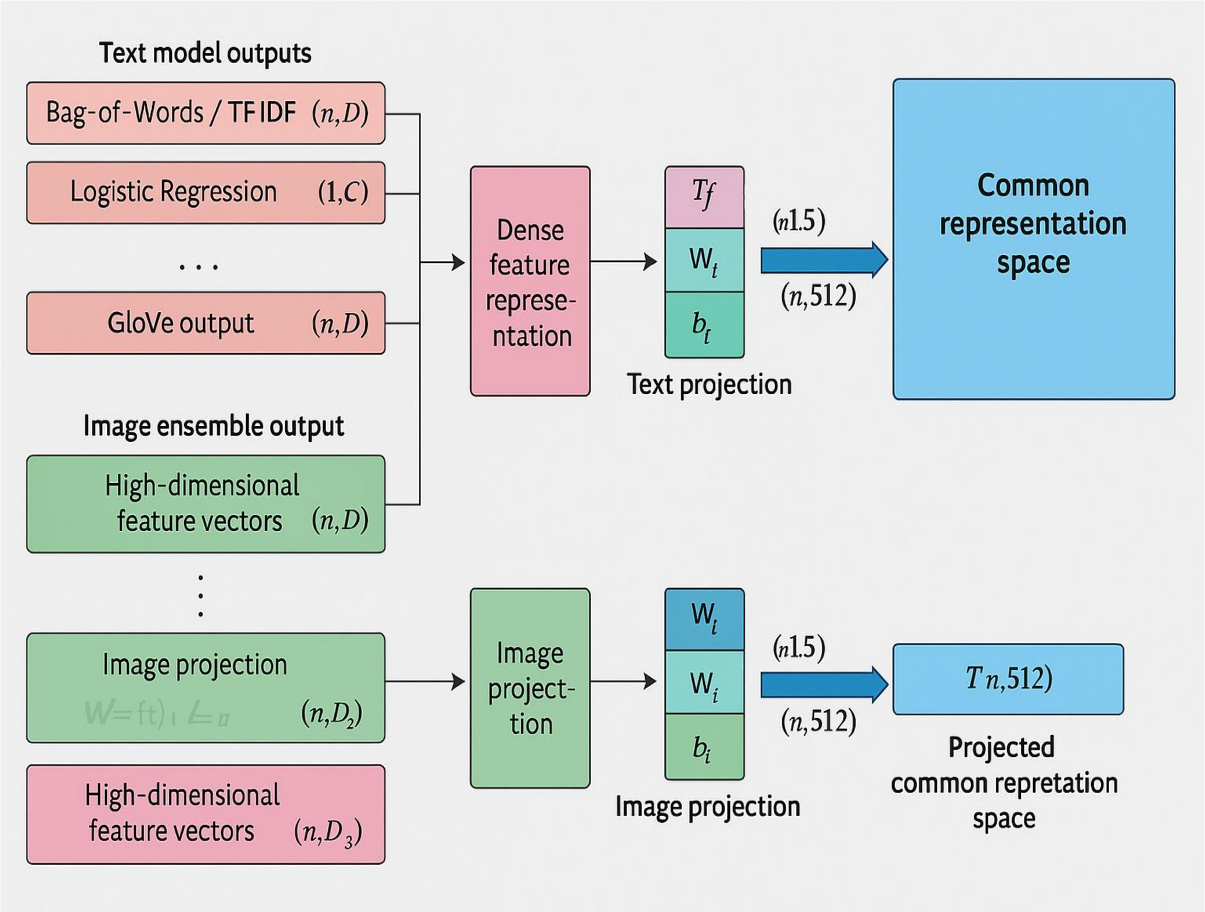
7. Fusion strategy–Integrated Modalities

Text
Tokenization/Stopword Removal/Lemmatization
Vectorization via BoW/TF-IDF (non-embedding)
Embeddings (GloVe)

Image
Resizing to 224×224
Normalization (0–1 range)
Feature extraction via ResNet50, DenseNet201.



7. Fusion strategy–Integrated Modalities



Textual Output:

Probabilistic outputs (non-embedding)-averaged

- Embedding outputs:
  - Word embeddings - averaged to form sentence vector
  - Dimensionality: (n,300) + (n,512) - concatenated - (n,812)

Image Output:

•High-dimensional deep feature vectors from CNNs

•Combined through ensemble - unified vector representation

- **Projection into Common Representation Space**

- **Projections - all** features (dense embeddings + probabilities) concatenated and projected into a common dense vector

8. Results and Evaluation-Evaluations Metrics

$$F(a) = \begin{cases} fake & if\ S(a) > \tau \\ not\ fake & otherwise \end{cases}$$

Each content item α gets a fake score S(α)∈[0,1]
Applied as threshold τ:

- Fake if S(α)>τ

Modality Scores:

- Text: Stext=Ftext(x;θ)
- Image: Simage=Fimage(f;θ)

Dynamic Fusion – Based on Confidence:

- f(x)=α(x)ftext(x)+β(x)fimage(x)
- Weights α(x),β(x) adjusted based on model confidence

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

$$Recall = \frac{TP}{TP+FN}$$

$$Precision = \frac{TP}{TP+FP}$$

$$F1\ Score = 2\frac{(Precision\ \times\ Recall)}{Precision + Recall}$$

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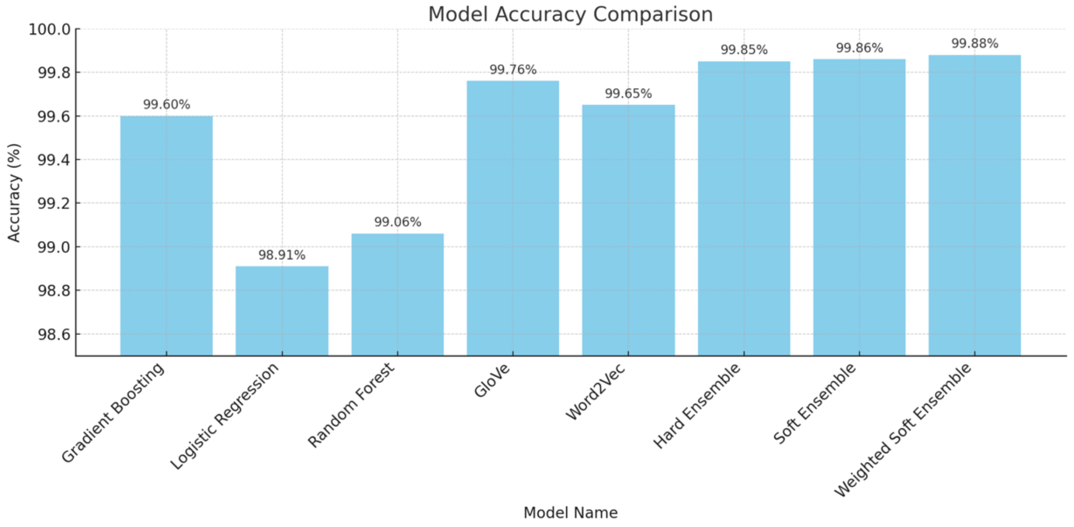
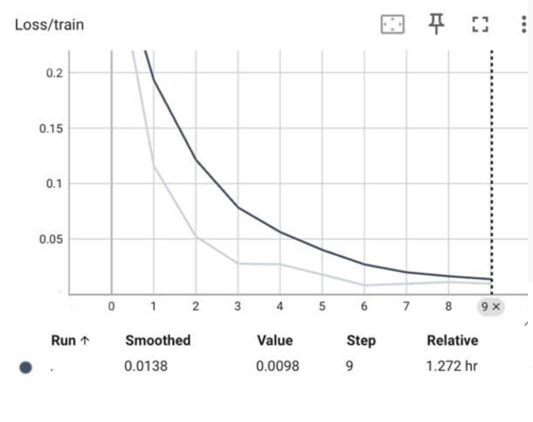
8. Results and Evaluation- Textual Model Results





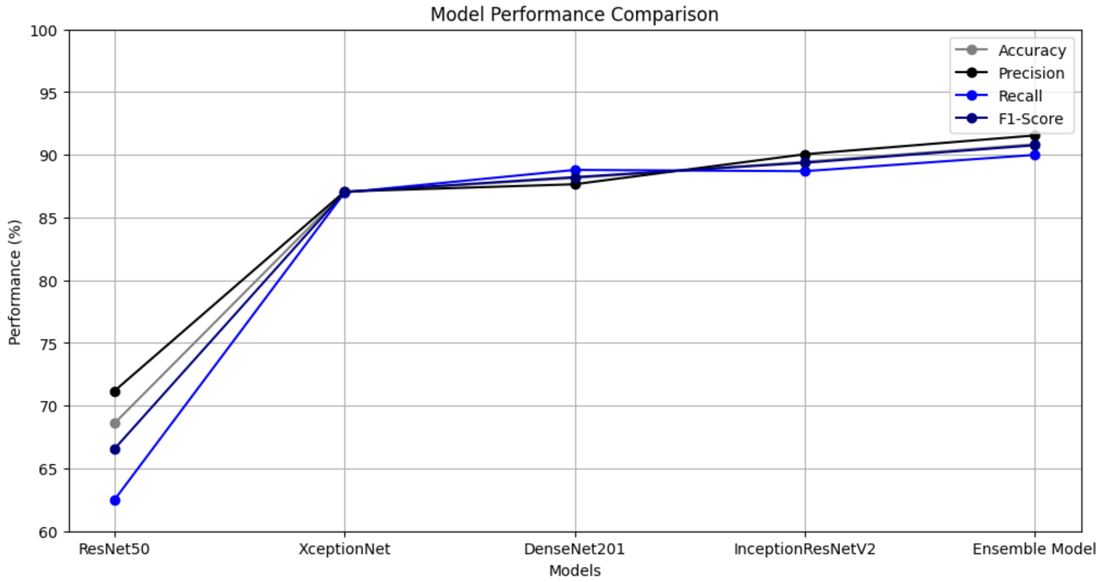

```
%%time

text = """

Global population growth is now slowing rapidly. Will a falling population be better for the environment?

Right now, human population growth is doing something long thought impossible – it's wavering. It's now possible global population could peak much earlier than e
In wealthier countries, it's already happening. Japan's population is falling sharply, with a net loss of 100 people every hour. In Europe, America and East Asia
This is an extraordinary change. It was only ten years ago demographers were forecasting our numbers could reach as high as 12.3 billion, up from around 8 billio
For 50 years, some environmentalists have tried to save the environment by cutting global population growth. In 1968, The Population Bomb forecast massive famine
Now we face a very different reality – population growth is slowing without population control, and wealthy country populations are falling, triggering frantic b
For much of Europe, North America, and some of Northern Asia, depopulation has been underway for decades. Fertility rates have fallen steadily over the past 70 y
China was until recently the world's most populous nation, accounting for a sixth of the global population. But China, too, is now declining, with the fall expec
By the end of the century, China is projected to have two-thirds fewer people than today's 1.4 billion. The sudden drop is due to the long tail of the One Child
For now, Tokyo's Shibuya Crossing is one of the busiest in the world. But depopulation is beginning to hit Japan hard. Takashi Images/Shutterstock
What's going on is known as demographic transition. As countries move from being largely rural and agrarian to industrial and service-based economies, fertility
Why? A major factor is choice for women. Women are increasingly having children later in life and having fewer children on average, due to improved choices and f
Why are we suddenly focused on depopulation, given birth rates in rich countries have been falling for decades? When the COVID pandemic hit in 2020, birth rates
A falling population poses real challenges economically. There are fewer workers available and more very old people needing support.Countries in rapid decline ma
Are these just rich country problems? No. Population growth in Brazil, a large middle-income country, is now the slowest on record. By 2100, the world is expecte
For instance, the per capita amount of energy we use peaks between ages 35 and 55, falls, and then rises again from age 70 onwards, as older people are more like
Then there's the huge disparity in resource use. If you live in the United States or Australia, your carbon footprint is nearly double that of a counterpart in C
Richer countries consume more. So as more countries get wealthier and healthier but with fewer children, it's likely more of the global population will become hi
Expect to see more liberal migration policies to boost the numbers of working-aged people. We're already seeing this – migration has now passed projections for 2
When people migrate to a developed country, it can be economically advantageous to them and the adopted country. Environmentally, it can increase per capita emis
As populations fall, countries will compete for skilled migrants. PeopleImages.com – Yuri A/Shutterstock. Then there's the looming upheaval of climate change. As
These factors aside, it's possible a falling global population could cut overall consumption and reduce pressure on the natural environment.
Environmentalists worried about overpopulation have long hoped for global population to fall. They may soon get their wish. Not through enforced birth control po
It's very much an open question whether falling populations will reduce pressure on the natural world. Unless we also cut emissions and change consumption patter


"""

res = weighted(text)
res
```

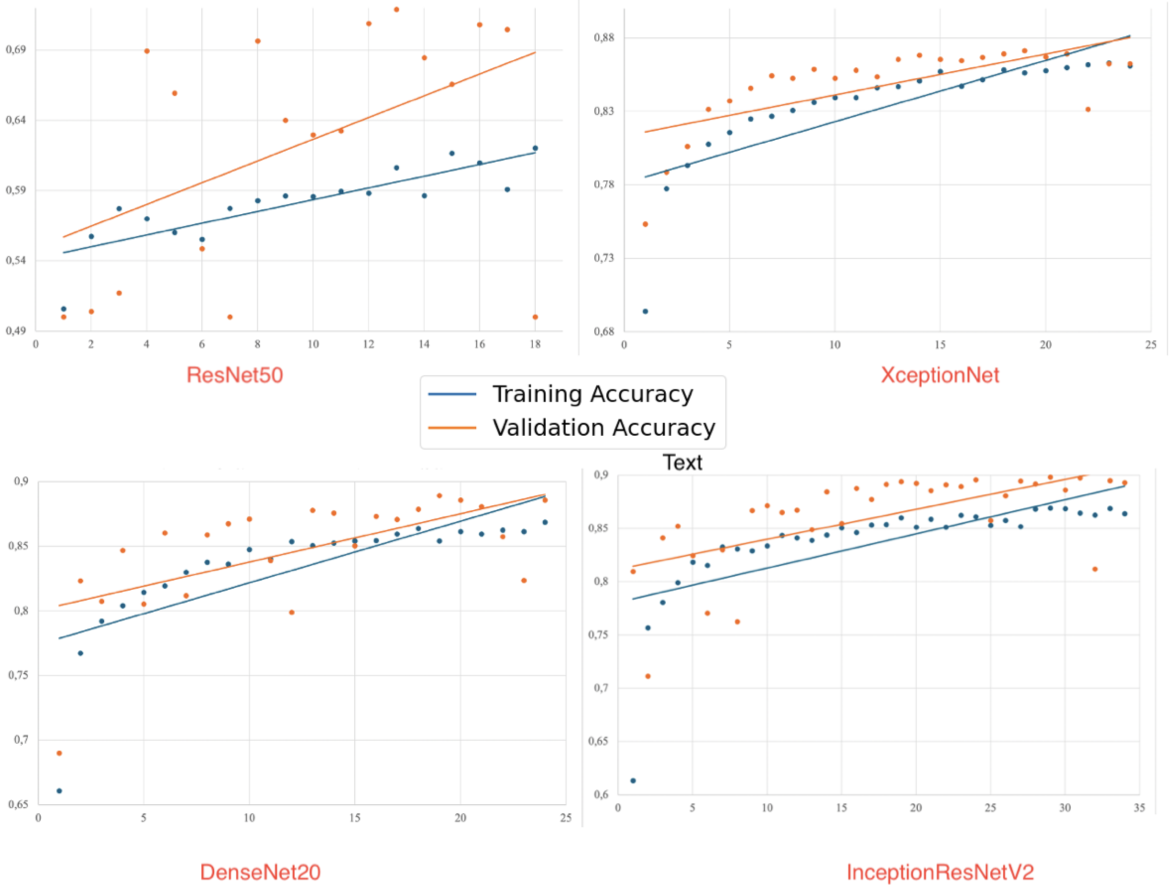
```
CPU times: user 708 ms, sys: 45.4 ms, total: 753 ms
Wall time: 605 ms
'More likely to be true'
```

8. Results and Evaluation-Visual Model Results

Optimisation Techniques

- Overfitting prevention: Early stopping, regularisation, dropout
- Data augmentation: Rotation, zoom, flip, brightness, shear
- Hyperparameter tuning: Talos library





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8. Results and Evaluation-Visual Model Results

The Ensemble Model outperforms all individual models

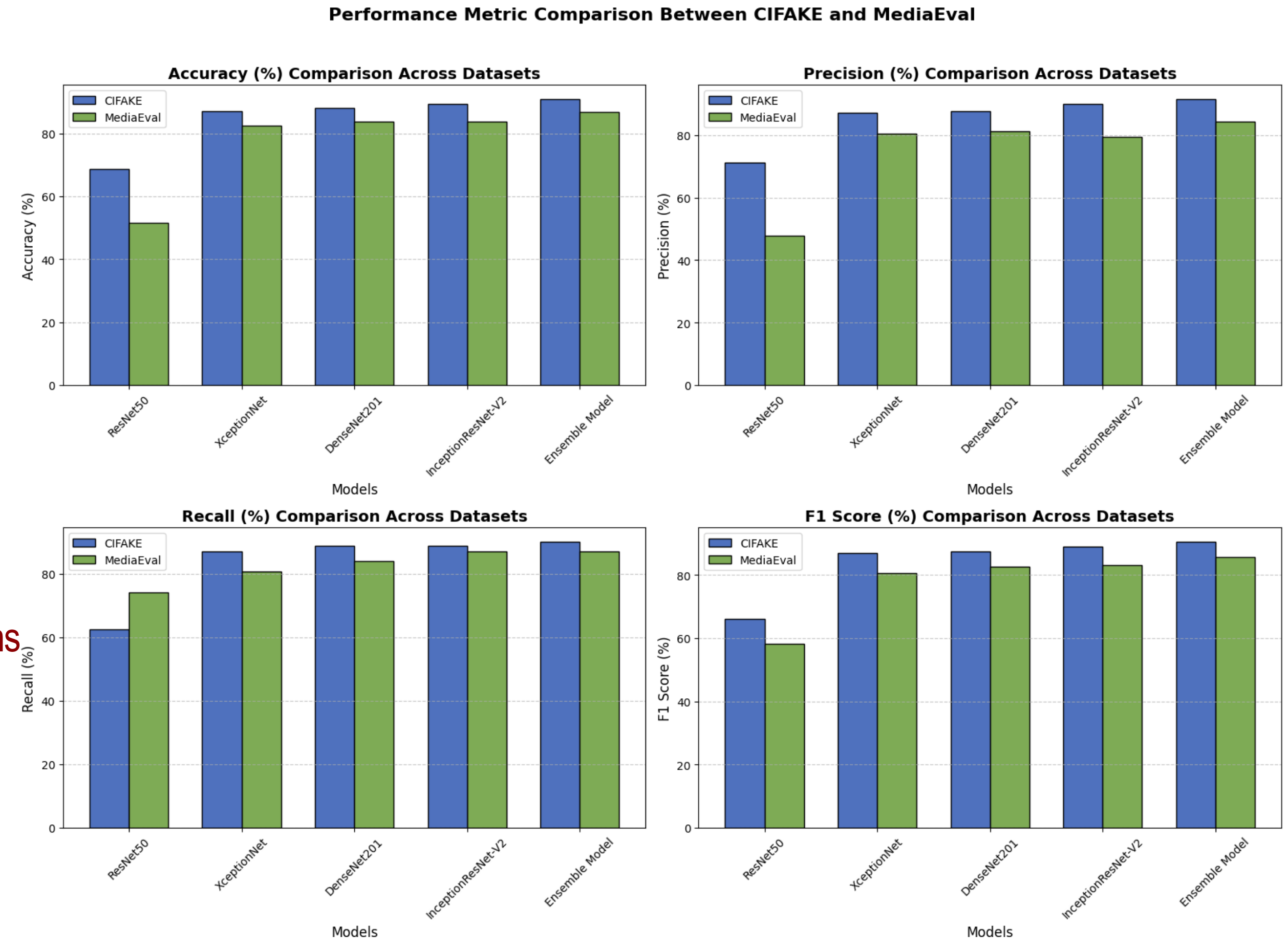
•Using majority voting across models

Best Individual Model

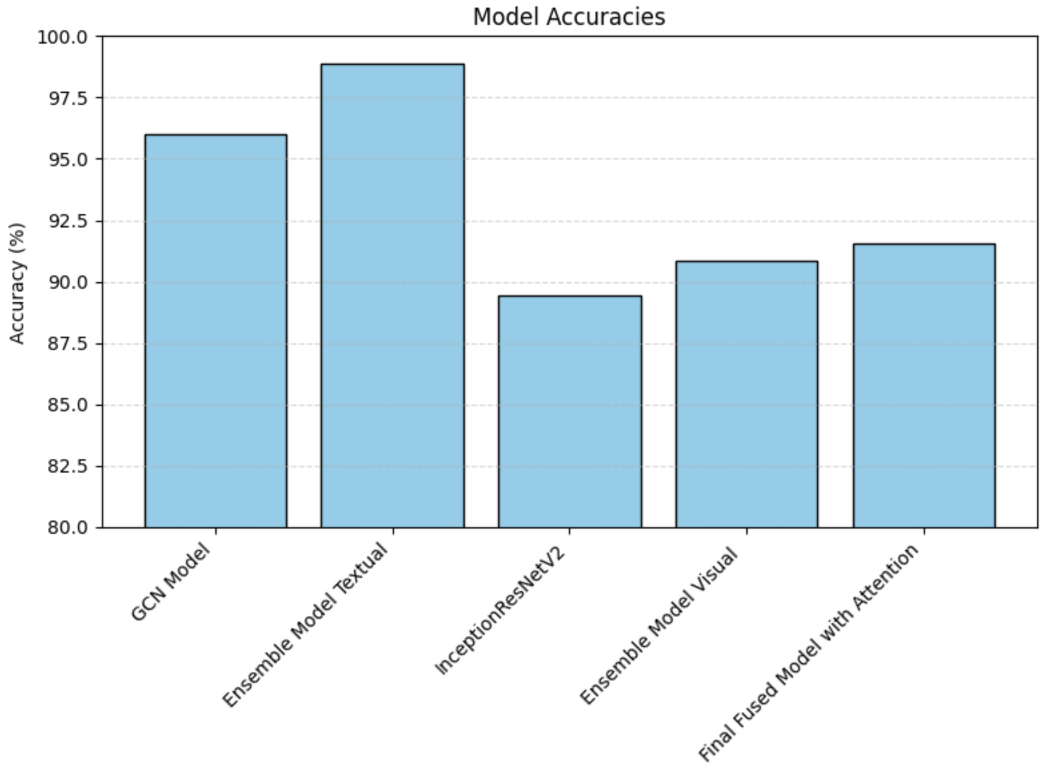
•InceptionResNetV2

- Accuracy: 89.45%, F1-score: 89.37%
- High Precision (90.05%) and Recall (88.70%)
- Combines Inception modules + Residual connections
- Strong performance with lower complexity than ensemble

Worst performing: ResNet



8. Results and Evaluation-Fused Model Results



Model	**F1 Score**
SpotFake [174]	0.89
EANN [194]	0.71
MVAE [90]	0.74
Vgg16-BERT [106]	0.89
BERT-CNN-Attention[175]	0.81
3-image-vgg16-LSTM+BERT+similarity+fusion [53]	0.79
FNDB [111]	0.88
MMAFake2D (Fusion with Attention)	**0.91**

9. Discussion of the results in the light of the research goals

RG1:

- Dominance of unimodal approaches–Most studies focus on text-only or image-only detection.
- Limited adoption of multimodal methods, despite their potential to improve accuracy and contextual understanding.
- Text-based models (especially NLP) have shown strong progress, but still struggle with context and ambiguity.
- Visual models (CNN-based) detect manipulated images effectively but require large, diverse datasets and are computationally intensive.
- Lack of comprehensive multimodal integration (text + image).
- Static weighting methods in current fusion models lead to imbalanced results.
- Insufficient handling of big data modality integration and dynamic fusion strategies.

9. Discussion of the results in light of the research goals

RG2:

- Empirical evidence from GCN-based models supports the hypothesis that graph-based methods alone are sufficient for fake news detection.
- Training accuracy consistently exceeded 90%, and validation accuracy remained above 95%, demonstrating high reliability.
- Performance remained robust across variable data conditions, with fluctuations in loss attributed to data noise and distribution changes, not model limitations.
- Overfitting was effectively mitigated, supported by stable accuracy trends and loss behaviour throughout training.
- Effective summarisation of tweet network structures (retweets, mentions, replies) confirmed that relational and topological features carry strong discriminative power.

9. Discussion of the results in light of the research goals

RG3:

- Modality-Specific Architecture: Separate models for text (articles/tweets) and images were first developed and optimised individually before being fused. This modular design preserved the individual strengths of each modality, aligning with the hypothesis that multi-module systems improve performance.

- Fusion Technique: The study applied late fusion (processing each modality separately, then combining predictions), achieving 91.55% accuracy and 90% F1-score.This proves the hypothesis that balanced fusion techniques enhance detection by leveraging complementary information from each data type.

- Dynamic Weighting Mechanism: Predictions were weighted based on confidence scores, adjusting each modality's influence dynamically. This adaptability confirms the hypothesis that context-sensitive fusion increases reliability and robustness of the detection system.

9. Discussion of the results in light of the research goals

RG3:

- Ensemble Learning on Visual Data: For image-based detection, multiple CNNs (ResNet50, DenseNet201, XceptionNet, InceptionResNetV2) were integrated via bagging (majority voting).

- The ensemble model outperformed individual models, achieving 90.85% accuracy vs. 89.45% (best single model), supporting the hypothesis that ensemble learning captures more complex patterns.

- Performance vs. Efficiency Insight: The study acknowledges that while the ensemble shows superior performance, computational trade-offs suggest single models (e.g., InceptionResNetV2) might be more practical in resource-constrained settings. This nuanced evaluation supports the hypothesis while recognising operational constraints.

10. Limitations

- High Computational Costs: Fusion techniques (late fusion, ensemble models) demand significant resources, limiting scalability and flexibility.
- Limited Modalities: Only text and visual data were integrated; audio/video modalities were excluded due to time/resource constraints.
- Training Data Bias: Model performance may still be influenced by biases in datasets, impacting generalisation across contexts.
- Interpretability Challenges: Fusion models, while effective, can become less transparent, especially with more than two modalities.
- Late fusion may lack deep integration of low-level modality interactions. The choice of attention type can significantly impact both performance and efficiency and requires trade-offs.

10. Future Avenues

- Optimisation of fusion methods to reduce computational load without sacrificing performance.
- Expanding multimodality to include audio/video, with adaptable fusion strategies.
- Techniques to detect and mitigate data biases and improve cross-domain generalisation.
- Improved transparency and explainability in complex fusion and ensemble models.
- Focus on real-time adaptability for faster, scalable deployment in dynamic information ecosystems.

Research contributions

Hasimi, L., & Poniszewska-Maranda, A. "A Systematic Study on Fake News and Disinformation Detection Using Machine Learning." **ACM Computing Surveys** (Status: Second-round review).

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Thank you for your attention!

Q&A