Automated Scientific Paper Classification

A Machine Learning Approach to arXiv Category Prediction

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*Abstract*—This report presents an automated classification system for categorising arXiv scientific papers across eight major disciplines using machine learning techniques. Working with a dataset of over 860,000 papers (sampled to 59,000 for computational feasibility), we developed models to classify journal papers into Physics, Mathematics, Computer Science, Quantitative Biology, Statistics, Electrical Engineering, Quantitative Finance, and Economics categories. Our methodology covers the complete machine learning pipeline from data collection through model evaluation, aiming to enhance academic information management by improving paper organisation and discovery, ultimately facilitating interdisciplinary research and literature navigation in an increasingly complex scientific landscape.

# Introduction

Classifying scientific papers into their respective research domains is critical in academic information management. As the volume of scientific literature grows exponentially, automated classification systems become increasingly important for organising, discovering, and analysing research papers effectively. This project focuses on developing and evaluating machine learning models for automatically classifying scientific papers from arXiv, one of the largest repositories of electronic preprints.

Our work addresses the challenge of multi-class classification across eight major scientific disciplines: Physics, Mathematics, Computer Science, Quantitative Biology, Statistics, Electrical Engineering, Quantitative Finance, and Economics. By leveraging modern natural language processing techniques and machine learning algorithms, we aim to create a robust classification system that can accurately categorise papers based on their content, helping researchers and institutions better manage and navigate the vast landscape of scientific literature.

The significance of this project extends beyond mere organisational benefits. Accurate classification of scientific papers facilitates interdisciplinary research by helping researchers discover relevant work across different fields. It also enables a better understanding of research trends and the evolution of scientific disciplines over time. Furthermore, automated classification systems can help identify emerging research areas and cross-disciplinary connections that are not immediately apparent through traditional categorisation methods.

This report presents our comprehensive approach to building and evaluating such a classification system. We detail our methodology from data collection and preprocessing to model development and evaluation, providing insights into both the technical challenges encountered and the solutions implemented. Our findings contribute to the broader understanding of automated scientific document classification and offer practical insights for similar applications in academic content management.

# Data Scraping

Our initial dataset comprised 863,251 scientific papers from arXiv. However, due to computational constraints, we sampled this down to a more manageable size of 58,816 papers. This sampled dataset was then split into training, validation, and test sets containing 37,142, 15,795, and 5,879 papers, respectively, following standard machine learning practices for model development and evaluation.

Figure 1 above shows considerable variation across the eight scientific disciplines. Physics papers comprised 26,674, followed by Mathematics and Computer Science, with 13,794 and 12,680 papers, respectively. The remaining categories had significantly smaller representations: Quantitative Biology contained 1,861 papers, Statistics had 1,341 papers, and Electrical Engineering included 1,337 papers. The smallest categories were Quantitative Finance and Economics, with 821 and 308 papers, respectively.

This imbalanced distribution reflects the historical development and relative sizes of different research communities on arXiv, which originated primarily as a physics preprint server before expanding to other fields. The significant class imbalance presented a vital consideration for our modelling approach, requiring careful handling to ensure fair treatment of minority classes during classification.

## Data Collection

The data collection process used the arXiv Python package to interface with the arXiv API. This package provided a robust and efficient way to programmatically access the vast repository of scientific papers hosted on arXiv. The package's implementation handled rate limiting and connection management, allowing us to collect data reliably at scale.

We focused our data collection efforts on eight primary research categories representing distinct scientific domains: Physics, Mathematics, Computer Science, Quantitative Biology, Quantitative Finance, Statistics, Electrical Engineering and Systems Science, and Economics. We deliberately selected these specific categories to create a dataset encompassing a broad spectrum of scientific research while maintaining clear categorical boundaries.

The chosen categories represent traditional scientific fields like Physics and Mathematics as well as emerging interdisciplinary areas such as Quantitative Finance and Quantitative Biology. This diversity was crucial for developing a classification system that could effectively handle the varied nature of modern scientific research. Each category contains numerous subcategories, providing fine-grained classification possibilities while maintaining clear parent category distinctions.

## Data Validation

To build our dataset, we systematically extracted key metadata fields for each paper in the arXiv repository. These fields included the paper's title, summary/abstract, authors, category, comments, and publication date. This comprehensive set of metadata provided the foundation for our subsequent analysis and classification tasks.

The extracted text data required careful cleaning and standardisation to ensure consistency across the dataset. We addressed encoding issues by standardising all text to UTF-8 and Windows-1252 encodings, which helped resolve character rendering problems common in academic texts. Line breaks within paper summaries were eliminated to create uniform, continuous text blocks that would be easier to process. Additionally, we consolidated author names into single, comma-separated strings to simplify the data structure while preserving all contributor information.

To streamline our classification approach, we systematically mapped specific arXiv categories to their broader parent categories. For example, specialised subcategories like "cs.AI" (Artificial Intelligence) were mapped to their parent category "Computer Science." This hierarchical organisation helped maintain clear categorical boundaries while reducing the complexity of our classification task.

## Data Creation

The creation of our dataset involved several critical steps to ensure the quality and usability of the data for machine learning tasks. First, we removed duplicate papers based on their unique arXiv IDs to remove any redundant entries that may have been collected during the scraping process. This step was essential to prevent data leakage and ensure the integrity of our subsequent analysis.

After deduplication, we carefully divided our dataset into three subsets to support proper model development and evaluation. The training set, comprising 63% of the data, served as the primary dataset for model training. We allocated 27% of the data to the validation set, which was used to tune model parameters and prevent overfitting during the training process. The remaining 10% was reserved for the test set, providing an unbiased evaluation of the final model performance.

To maintain the representativeness of our data across all subsets, we implemented stratified splitting based on paper categories. This stratification ensured that the distribution of research categories remained consistent between the training, validation, and test sets, preventing potential bias in our model evaluation. The final dataset, containing 863,251 papers, was saved in CSV format to facilitate easy access and further processing during subsequent stages of our research.

These careful preparation steps established a robust foundation for our model development and analysis work. The resulting datasets were well-structured and adequately balanced, enabling reliable training and evaluation of our classification models.

## Error Handling

The error-handling mechanisms were robustly designed to ensure the reliability and integrity of the data collection process. We implemented a comprehensive retry mechanism to handle transient API errors, which proved essential in maintaining uninterrupted data collection despite temporary network or service issues. This mechanism automatically attempted to reconnect and resume data collection after encountering errors, significantly reducing manual intervention requirements.

Empty API responses presented another critical challenge that we addressed through careful implementation of checks and fallback procedures. When the API returned no data for a particular request, our system logged these instances and implemented appropriate fallback strategies to ensure the continuity of the data collection process. This approach helped maintain the completeness of our dataset while providing clear documentation of any gaps in the collected data.

Due to the diverse nature of scientific content, text encoding posed a significant challenge. We addressed this by implementing standardised UTF-8 encoding across all collected text data. This standardisation process involved carefully handling special characters and symbols familiar in scientific papers, ensuring that mathematical notation and technical symbols were preserved accurately in our dataset.

Data quality was maintained through rigorous handling of the dataset's NaN (Not a Number) values. Rather than allowing these null values to propagate through our analysis pipeline, we implemented systematic identification and removal procedures. This approach helped maintain the integrity of our dataset while preventing potential issues during subsequent analysis stages.

We implemented a comprehensive warning system to identify and address potential data quality issues proactively. This system monitored various aspects of the data collection process and flagged potential problems for review. These warnings covered unusual text patterns, unexpected category assignments, and possible data inconsistencies, allowing us to quickly identify and resolve issues before they could impact our analysis.

# Data Preprocessing

The data preprocessing pipeline, implemented in data\_preprocessing.py, is the foundation for preparing our dataset for subsequent analysis and modelling tasks. This pipeline incorporates comprehensive text processing and data cleaning operations to ensure data quality and consistency.

The preprocessing workflow was carefully structured to handle the complexities inherent in scientific text data while preserving the semantic meaning crucial for accurate classification. Our implementation focused on efficiency and effectiveness, utilising modern natural language processing techniques and robust error-handling mechanisms.

Through this pipeline, we systematically transformed raw text data into a clean, standardised format suitable for machine learning applications. The following sections detail the specific steps and techniques used in our preprocessing approach.

## Text Cleaning

Our text cleaning process involved several comprehensive steps to ensure data quality and consistency. First, we standardised category names by mapping them to our eight primary research categories, creating a unified classification system. We then performed thorough duplicate detection and removal by comparing titles, summaries, and comments across entries to maintain data integrity.

We systematically removed rows containing missing values to ensure the dataset was complete. The text normalisation process began by converting all text to lowercase for uniformity. It was followed by carefully removing punctuation marks while preserving the semantic meaning of the content. We also excluded numeric characters from text fields that weren't essential to the meaning.

Whitespace management was another crucial aspect, involving removing excessive spaces and standardising spacing throughout the text. Using NLTK, we eliminated common English stop words to reduce noise in our text data. We also expanded contractions to their whole forms (e.g., "don't" to "do not") to maintain consistency in word representation.

The cleaning continued, with diacritical marks converted to standard characters and special characters carefully removed while maintaining text integrity. Modern text elements such as emojis and emoticons were removed from the dataset as they weren't relevant to scientific content. We also stripped any HTML tags and URLs that appeared in the text.

Finally, we standardised all text encoding to UTF-8 format, ensuring consistent character representation across the entire dataset. This comprehensive text-cleaning approach created a standardised, high-quality dataset suitable for our machine-learning tasks while preserving the essential meaning of the scientific content.

## Implementation Details

Implementing the preprocessing pipeline leveraged several essential libraries and techniques to ensure efficient and effective text cleaning and preparation. At the core of our data processing workflow, we utilised pandas for efficient manipulation and handling of large datasets. This choice was crucial given the substantial size of our arXiv paper collection and the need for performant data operations.

We used the NLTK and spaCy libraries for natural language processing tasks. These libraries provided comprehensive tokenisation, lemmatisation, and stop-word removal functionality. These NLP operations were essential for deconstructing the scientific text into meaningful components that our models could effectively analyse.

Regular expressions played a vital role in our text-cleaning process. We implemented carefully crafted regex patterns to identify and clean specific text patterns, including URLs, HTML tags, and special characters that could introduce noise into our analysis. This systematic approach ensured consistency in handling various text elements across the entire dataset.

To maintain the integrity of the scientific content, we implemented sophisticated noise reduction techniques that focused on preserving the semantic meaning of the text while removing irrelevant information. This balance was essential given the technical nature of the papers in our dataset.

Our pipeline included robust edge case handling to address various text encoding issues and unusual patterns that emerged during processing. This comprehensive approach to edge cases ensured that our preprocessing remained reliable across our dataset's diverse range of scientific papers.

The preprocessing steps were applied to key text columns, including title, summary, comment, and authors. Each field required specific consideration to prepare them appropriately for downstream analysis and modelling tasks while maintaining their distinct characteristics and importance to the classification process.

## Data Quality

The preprocessing pipeline incorporated several measures to ensure high data quality throughout our dataset preparation process. A key focus was maintaining consistent formatting across all text fields, facilitating seamless analysis in later stages. We implemented careful text-cleaning procedures that preserved the semantic integrity of the content, ensuring that the original meaning and value of the scientific information remained intact even as we standardised the format.

Our pipeline was designed with robust multilingual support capabilities, allowing us to effectively process text in multiple languages without losing meaning or accuracy. This was particularly important given the international nature of scientific research and the diversity of our dataset. We developed sophisticated character and symbol removal procedures that eliminated unnecessary elements that could introduce noise while carefully retaining characters essential to scientific notation and technical content.

Throughout the preprocessing steps, we maintained a standardised approach to text representation. This consistency was vital for ensuring that all documents, regardless of their source or original format, were transformed into a uniform structure suitable for machine learning applications. The standardisation process was carefully calibrated to preserve the nuanced technical language common in scientific papers while removing irrelevant variations in formatting and presentation.

These comprehensive quality control measures were instrumental in producing a clean, standardised dataset that retained the essential semantic content required for downstream machine learning tasks. Each preprocessing step was meticulously designed and tested to ensure it struck the right balance between noise removal and content preservation, ultimately maintaining the interpretability and integrity of the scientific papers while preparing them for practical analysis.

# Data Exploration

The data exploration phase was a critical step in understanding the characteristics and patterns within our dataset. Through comprehensive analysis, we gained valuable insights into our scientific paper collection's distribution, composition, and unique attributes.

Our exploration focused on several key aspects: the overall size and composition of the dataset, the distribution of papers across different scientific categories, and the statistical properties of various text fields. This systematic investigation allowed us to identify meaningful patterns and potential challenges influencing our subsequent modelling decisions.

The analysis revealed significant insights into class imbalances, text length distributions, and the relationships between paper attributes. These findings were instrumental in shaping our approach to model development and evaluation, ensuring that our methodology effectively addressed the specific characteristics of the dataset.

## Dataset Overview

Our dataset analysis revealed comprehensive information about each column's characteristics and data quality. The title column contains 58,816 entries with nearly unique values (58,791 unique titles), indicating minimal duplication. Among the few repeated titles, papers on quantum mechanics, confidence intervals, and particle dynamics appeared multiple times, suggesting these are common research areas or potential variations of similar works.

The summary field demonstrates similar characteristics, with 58,793 unique entries out of 58,816. Notably, several withdrawn papers are in the dataset, with "paper withdrawn" being the most common summary text. This transparency in documenting withdrawn papers contributes to the dataset's integrity. The summaries vary significantly in length and content, from brief withdrawal notices to detailed technical descriptions of research methodologies and findings.

The comment field shows more standardised patterns, with common formatting conventions emerging. The most frequent comment type is "pages figures" (10,016 occurrences), followed by simply "pages" (6,764 occurrences). This standardisation suggests a common documentation practice across submissions, though with varying levels of detail in structural descriptions.

Author distribution analysis reveals interesting patterns in academic publishing. While most authors appear infrequently, there are notable prolific contributors. Lorenzo Iorio leads with 23 papers, followed by B G Sidharth with 18 papers. Large collaboration groups, such as the OPAL and BABAR collaborations, also feature prominently in the dataset, reflecting the collaborative nature of modern scientific research.

The category distribution confirms our earlier observations about class imbalance. Physics dominates with 26,674 papers, followed by Mathematics (13,794) and Computer Science (12,680). Smaller categories like Quantitative Biology (1,861) and Statistics (1,341) have significantly less representation, highlighting the need for careful consideration in our modelling approach to handling this imbalance.

Finally, the dataset split follows a conventional machine learning practice with a train/validation/test ratio of approximately 63/27/10 (37,142/15,795/5,879 samples, respectively). This split provides sufficient data for model training while maintaining adequate validation and test sets for robust performance evaluation.

## Category Distribution

Analysis of the category distribution reveals significant imbalances across different academic disciplines in our dataset. Physics is the dominant category, comprising nearly half (45.4%) of all papers with 26,674 entries. This substantial representation reflects the historically strong presence of physics research in academic publishing and preprint servers. The prevalence of physics papers may be attributed to the field's long-standing culture of preprint sharing, dating back to the original arXiv platform's roots in the physics community.

Mathematics and Computer Science form the next tier, with 13,794 (23.5%) and 12,680 (21.6%) papers, respectively. Together with Physics, these three fields account for over 90% of the dataset, highlighting a clear skew toward mathematical and computational sciences. This concentration suggests a strong interdisciplinary relationship between these fields, particularly in theoretical physics and computational modelling. The similar volumes of mathematics and computer science papers also indicate the growing importance of computational approaches in modern research.

The remaining categories have considerably smaller representations, forming a distinct third tier in the distribution. Quantitative Biology contains 1,861 papers (3.2%), reflecting the emerging nature of computational approaches in biological sciences. Statistics and Electrical Engineering have similar volumes, with 1,341 (2.3%) and 1,337 (2.2%) papers, respectively, suggesting these fields may have alternative preferred publishing venues. Quantitative Finance comprises 821 papers (1.3%), while Economics has the smallest representation, with just 308 papers (0.5%), potentially indicating that researchers in these fields favour traditional journal submissions over preprint platforms.

This pronounced class imbalance presents important considerations for our modelling approach, particularly ensuring fair representation and preventing bias toward the dominant categories. Our methodology will need special attention to address these distributional disparities while maintaining model performance across all categories. Potential strategies might include oversampling minority classes, implementing class weights, or using specialized architectures to handle imbalanced datasets. The imbalance also suggests that evaluation metrics should be carefully chosen to provide meaningful insights across all categories, regardless of their size.

The distribution pattern also offers valuable insights into the academic publishing landscape and the adoption of preprint platforms across different disciplines. It highlights how different fields have embraced open science practices at varying rates, with some disciplines showing stronger preferences for traditional publishing routes. This understanding could be valuable for both interpreting our results and considering the broader implications of our classification system.

## Data Quality Assessment

The dataset demonstrates exceptional quality across several key dimensions. A comprehensive analysis reveals that all critical fields are complete, with no missing values detected across the 471,879 records. This completeness ensures reliable analysis and model training without the need for complex imputation strategies.

The category labelling system maintains strict consistency throughout the dataset, with each paper properly assigned to one of the eight major academic fields. This standardisation is crucial for accurate classification tasks and cross-category analysis.

Text fields throughout the dataset exhibit well-formatted content, with proper character encoding that correctly handles special characters, mathematical symbols, and international author names. This formatting consistency facilitates effective text processing and analysis without extensive cleaning operations.

A thorough duplicate check confirms that each entry in the dataset is unique, eliminating any concerns about data redundancy that could skew analysis results or introduce bias into model training. This uniqueness and other quality factors provide a solid foundation for robust machine learning applications.

## Text Length Analysis

Our analysis of text length characteristics across different categories provides valuable insights into how various academic disciplines structure their papers. The following table presents the average character length for titles, summaries, and comments across the eight major categories in our dataset. These metrics offer a quantitative perspective on communication styles and documentation practices across disciplines.

The text length analysis reveals notable variations across different academic disciplines in how they structure their titles, summaries, and comments. These differences likely reflect the distinct communication norms, complexity of concepts, and methodological approaches characteristic of each field.

Regarding title length, Electrical Engineering and Systems Science (74.83 characters) and Quantitative Biology (71.13 characters) demonstrate significantly longer titles than other fields. For Electrical Engineering, this may reflect the need to specify both the technical system being studied and the methodological approach, while in Quantitative Biology, longer titles likely arise from the need to identify both the biological system and the quantitative method being applied. In contrast, Mathematics shows notably shorter titles (52.24 characters), possibly reflecting the field's preference for concise, abstract representations of concepts.

Summary lengths show even more pronounced variations. Quantitative Biology has the longest summaries (897.44 characters), followed closely by Electrical Engineering (882.93 characters) and Statistics (813.17 characters). The extended length of Quantitative Biology summaries might be attributed to the need to describe complex biological systems alongside mathematical methodologies. Mathematics has the shortest summaries (439.31 characters), which reflects the field's reliance on formal mathematical notation (not captured in character counts) and its tendency toward precise, economical expression.

Computer Science shows the longest average comment length (46.86 characters), followed by Physics (44.28 characters) and Statistics (44.49 characters). This pattern might reflect these fields' strong preprint culture and emphasis on implementation details or experimental conditions. The longer comments in Computer Science papers could indicate additional information about code availability, computational requirements, or implementation details. Quantitative Finance shows the shortest comments (34.48 characters), possibly due to the field's recent adoption of the preprint system and different commenting conventions.

These variations in text length metrics provide valuable insights into different academic disciplines' communication patterns and documentation requirements. The differences likely arise from a combination of historical conventions, practical necessities, and the inherent complexity of conveying discipline-specific concepts effectively.

## Word Frequency Analysis

Word frequency analysis reveals distinctive patterns in vocabulary usage across different academic disciplines. After removing common stop words, we identified the most frequently occurring terms in each category's papers. This analysis provides insights into each field's key concepts, methodologies, and focus areas.

The analysis of top words across different scientific categories reveals fascinating patterns in each field's focus and methodological approaches.

In Physics, "paper" is the most common word, indicating frequent references to prior work. Words like "quantum," "theory," and "energy" reflect the field's fundamental focus on understanding physical phenomena and developing theoretical frameworks. The high frequency of these terms aligns with physics' theoretical nature and its quest to explain the fundamental properties of matter and energy.

Mathematics shows a distinct pattern, with words like "prove," "space," and "show" dominating the top terms. This reflects the field's emphasis on formal proofs and abstract spaces. The prevalence of "prove" (3765 occurrences) particularly highlights the field's rigorous approach to establishing mathematical truths through logical argumentation.

Electrical Engineering and Systems Science demonstrates its applied nature through terms like "proposed", "model", and "system". The high frequency of "proposed" (1119 occurrences) suggests a strong focus on new methodologies and solutions, while "system" indicates the field's emphasis on integrated approaches to solving engineering challenges.

Computer Science has a clear data-centric focus, with "data" appearing 7468 times, the highest frequency among all terms across categories. The prominence of "model," "using," and "problem" reflects the field's emphasis on practical problem-solving and the implementation of solutions using various computational models.

Quantitative Biology's top terms—"model," "data," and "networks"—reveal its modern computational approach to biological research. The high frequency of "networks" (702 occurrences) particularly reflects the field's focus on understanding biological systems through network analysis and modelling.

Economics shows a strong theoretical foundation with "model" and "models" in its top terms, while "economic" and "data" reflect its empirical nature. The relatively lower frequencies (205 for "model") reflect the smaller dataset size but maintain similar thematic patterns to other quantitative fields.

Unsurprisingly, statistics centres around "data" (1658 occurrences) and various types of "models." The presence of "methods" and "method" in the top terms underscores the field's focus on developing and applying analytical techniques.

Quantitative Finance shows its specialised nature with domain-specific terms like "market", "financial", "price", and "risk". The high frequency of "model" (797 occurrences) indicates the field's heavy reliance on mathematical modelling for financial analysis.

Cross-category analysis reveals interesting patterns. "Model" appears as a top term in six out of eight categories, highlighting the ubiquity of modelling approaches across modern scientific disciplines. "Data" features prominently in computer science, statistics, and quantitative biology, reflecting the increasing importance of data-driven research methodologies. The term "paper" appears frequently in physics and computer science, suggesting strong citation cultures.

These patterns reflect the evolving nature of scientific research, where data-driven and computational methods across all disciplines increasingly complement traditional theoretical approaches. The analysis also reveals the distinct methodological signatures of each field while highlighting the growing convergence in analytical approaches across scientific domains.

## N-Gram Analysis

The n-gram analysis reveals distinctive linguistic patterns across scientific disciplines, highlighting key methodologies, tools, and research focuses. Common bi-grams and tri-grams provide insights into each field's characteristic terminology and conceptual frameworks. For example, physics papers frequently use phrases related to experimental methods ("monte carlo simulations"), theoretical concepts ("quantum field theory"), and physical phenomena ("magnetic field"). Economics papers show frequent use of analytical terms ("treatment effects") and economic concepts ("economic growth"). Quantitative biology demonstrates a strong focus on biological systems ("gene expression") and computational methods ("neural networks").

For detailed N-gram analysis across scientific disciplines, please refer to Appendix I.

## Topic Modelling

Topic modelling analysis was performed across all scientific disciplines to identify key research themes and methodological approaches. The study revealed distinct patterns of research focus and methodology unique to each field. For detailed topic modelling results and analysis across all scientific disciplines, please refer to Appendix II.

## Named Entity Recognition (NER)

The Named Entity Recognition (NER) analysis reveals distinctive patterns in how scientific disciplines use named entities in their research papers. The study shows that numerical entities (cardinal and ordinal numbers) dominate across fields, reflecting the quantitative nature of scientific research. However, each discipline exhibits unique characteristics in entity usage that align with their methodological approaches and research focuses.

For detailed Named Entity Recognition analysis results across all scientific disciplines, please refer to Appendix III.

### Sentiment Analysis

The sentiment analysis reveals subtle but notable variations in emotional tone across different scientific disciplines. Computer Science shows the highest average sentiment score (0.087), followed closely by Physics (0.093), suggesting these fields tend to use slightly more positive language in their research summaries. This could reflect the optimistic nature of technological advancement and physical discoveries or the tendency to emphasise positive outcomes and improvements in these fields.

Mathematics and Statistics demonstrate the lowest sentiment scores (0.071 and 0.070, respectively), indicating a more neutral tone in their research communications. This aligns with mathematical discourse’s traditionally objective and formal nature, where emotional language is typically minimised in favour of precise, technical expression.

The applied fields—Electrical Engineering and Systems Science (0.077) and Quantitative Finance (0.076)—show moderate sentiment scores, falling near the middle range. This might reflect a balance between technical objectivity and practical applications, where positive outcomes and real-world impacts are discussed alongside methodological details.

Economics (0.081) and Quantitative Biology (0.073) present interesting contrasts. Economics is more positive in its language, which could stem from discussions of positive economic outcomes, growth, or improvements in economic conditions. Meanwhile, Quantitative Biology maintains a more neutral tone typical of life sciences research.

Overall, the sentiment scores across all disciplines remain relatively close to neutral (ranging from 0.070 to 0.093), characteristic of academic writing. The small variations, while subtle, may reflect underlying differences in how different fields communicate their research findings and the balance they strike between objective reporting and highlighting positive outcomes or advances in their respective domains.

# Feature Engineering

Feature engineering is crucial in transforming raw text data into structured numerical features that machine learning models can effectively process. In this study, we implemented a comprehensive feature engineering pipeline that combines traditional NLP techniques with modern deep learning approaches to capture scientific papers’ semantic and statistical characteristics. The following sections detail the various feature extraction and transformation techniques applied.

## Tokenisation and Lemmatisation

The tokenisation and lemmatisation process was implemented using BERT (Bidirectional Encoder Representations from Transformers), leveraging its advanced contextual understanding of text structure. This approach offers several advantages over traditional lemmatisation methods:

First, BERT's bidirectional nature allows it to consider the full context when processing each word, leading to more accurate lemmatisation that accounts for word sense and usage. The model processes text through its transformer architecture, which helps maintain semantic relationships while reducing words to their base forms.

The implementation handles text processing in batches to optimise computational efficiency, with automatic memory management for CUDA-enabled systems. This batch-processing approach allows for the efficient processing of large text corpora while maintaining consistent quality. The system automatically adapts to available computational resources, utilising GPU acceleration when available and gracefully falling back to CPU processing when necessary.

Special attention was paid to maintaining text integrity during processing. The system preserves important linguistic features while removing unnecessary tokens and standardising text representation. This preprocessing step was applied to all text fields (titles, summaries, comments, and author lists) to ensure consistent treatment across the dataset.

The lemmatisation process helps reduce vocabulary size and standardise word forms, making subsequent analysis more reliable. This is particularly important for scientific text, where technical terms and their variants must be properly normalised while preserving their semantic meaning.

## Vectorisation

Text vectorisation was implemented using BERT embeddings to capture rich semantic representations of the scientific papers. The vectorisation process transforms text into high-dimensional numerical vectors that encode contextual meaning and relationships between words.

The implementation uses the 'bert-base-uncased' model to generate embeddings for each text field (titles, summaries, comments, and author lists). BERT's transformer architecture processes text bi-directionally, allowing it to capture complex contextual relationships and nuances in scientific writing. The model generates 768-dimensional vectors for each text input, representing dense semantic content.

The vectorisation process includes several optimisations for handling large datasets. Batch processing efficiently handles large volumes of text, while automatic memory management enables GPU acceleration when available. The system gracefully returns to CPU processing when needed, ensuring reliable processing regardless of hardware constraints. Truncation and padding mechanisms are employed to handle variable-length inputs properly, maintaining consistent vector dimensions across all samples.

Special attention was paid to maintaining consistent vector representations across different text fields. The process appropriately handles missing or malformed text, ensuring robust feature generation even with imperfect input data. The resulting embeddings capture the scientific text’s local syntactic patterns and broader semantic relationships.

These BERT embeddings provide a rich foundation for downstream machine learning tasks, encoding complex relationships between scientific concepts, methodologies, and findings. Their high-dimensional nature allows them to capture subtle variations in meaning that are particularly important in distinguishing between different scientific disciplines.

## Word Count

Word count analysis was performed on all text fields (titles, summaries, comments, and author lists) to quantify text length and verbosity. The implementation processes text in efficient batches of 1000 samples, splitting text on whitespace to count individual words.

For each text field, a new feature column is created containing the raw word count. This provides a basic but important metric of text length that can help distinguish between different types of scientific papers. For example, theoretical papers may tend toward longer, more detailed summaries than experimental papers.

The word-counting process incorporates several robustness features to ensure reliable processing. The system automatically handles non-string inputs by converting them to strings before processing and properly manages empty or malformed text to prevent errors. To maintain consistency, the counting methodology is standardised across all text fields in the dataset. Additionally, the implementation optimises performance through batch processing, allowing efficient handling of large volumes of text data.

While simple compared to semantic analysis, word counts provide valuable signals about paper structure and writing style. They can reveal patterns in how different scientific disciplines structure their abstracts and summaries, helping distinguish between fields that favour concise versus detailed descriptions.

The word count features complement the more sophisticated semantic features by explicitly quantifying text length. Combined with complexity metrics and semantic embeddings, this can be particularly useful for building a complete picture of paper characteristics.

## Named Entity Recognition (NER)

Named Entity Recognition was implemented using spaCy's pre-trained "en\_core\_web\_sm" model to identify and quantify different types of entities in the text. The implementation processes text in batches of 100 samples for optimal performance, analysing all text fields, including titles, summaries, comments, and author lists.

The system identifies and counts entities across multiple categories for each text field, including person names, organisations, locations, dates, and other domain-specific entities. The NER process creates separate count features for each entity type, allowing for fine-grained analysis of the content focus. This batch-processing approach ensures efficient handling of large text volumes while maintaining consistent entity recognition quality.

The implementation includes robust error handling and type conversion, automatically converting all text to strings before processing. Entity counts are aggregated per document and stored in dedicated columns following a standardised naming convention (e.g., 'title\_ner\_PERSON\_count', 'summary\_ner\_ORG\_count'). This structured approach enables detailed analysis of how different scientific disciplines use various named entities in their papers.

Entity recognition provides valuable insights into domain-specific terminology and focus areas of different scientific fields. For example, it can reveal patterns in how frequently papers reference specific organisations, locations, or key figures in their field. These entity patterns are important for distinguishing between scientific disciplines and complement the semantic and statistical features extracted through other methods.

## Sentiment Analysis

Sentiment analysis was performed using TextBlob to calculate polarity scores ranging from -1 (negative) to 1 (positive) for all text fields in the dataset. The implementation processes text in batches of 1000 samples for efficient computation, analysing titles, summaries, comments, and author lists.

For each text field, the system calculates a sentiment polarity score that captures the overall emotional tone of the text. The process automatically handles text preprocessing by converting all inputs to strings before analysis. The sentiment scores are stored in dedicated columns following a standardised naming convention (e.g., 'title\_sentiment', 'summary\_sentiment').

While scientific papers generally use neutral and objective language, subtle variations in sentiment can provide valuable signals for classification. For example, certain fields may use more positive language when describing results, while others maintain stricter neutrality. Sentiment features complement the semantic and statistical features by capturing these subtle emotional undertones in scientific writing.

The implementation includes robust error handling and parallel processing optimisations through the TOKENIZERS\_PARALLELISM environment variable. This ensures reliable and efficient sentiment analysis even with large volumes of text data. The resulting sentiment scores provide an additional dimension for distinguishing scientific disciplines based on their characteristic writing styles and emotional expression patterns.

## Text Complexity Metrics

Text complexity analysis was performed using the Automated Readability Index (ARI) to quantify the sophistication level of all text fields in the dataset. The implementation processes text in batches of 1000 samples, analysing titles, summaries, comments, and author lists.

For each text field, the system calculates an ARI score based on character count, word count, and sentence count using the formula: 4.71 \* (characters/words) + 0.5 \* (words/sentences) - 21.43. The scores are bounded between 1 and 14, with higher scores indicating more complex text. The implementation includes robust handling of edge cases, such as texts with no sentence-ending punctuation, and automatically converts all inputs to strings before analysis.

The ARI scores provide valuable insights into the linguistic complexity patterns across different scientific disciplines. For example, certain fields may consistently use more complex language in their titles or summaries than others. The implementation creates separate complexity features for each text field (e.g., 'title\_ari', 'summary\_ari'), enabling detailed analysis of how writing complexity varies across different parts of scientific papers.

These complexity metrics complement the semantic and statistical features by explicitly quantifying text sophistication. Combined with other features like word counts and entity recognition, they help build a comprehensive picture of the writing styles characteristic of different scientific fields.

## Feature Normalisation

Feature normalisation was implemented using scikit-learn's MinMaxScaler to transform all numerical features to a consistent [0,1] range. The normalisation process excludes the categorical target variable ('category') and split designation columns to preserve their original values. This scaling ensures that all numerical features contribute proportionally to model training, preventing features with larger absolute values from dominating the learning process.

The implementation automatically identifies numerical columns by their data type (int64 or float64) and applies the scaler transformation. The MinMaxScaler preserves zero values and the shape of the original distribution while bounding all values between 0 and 1. This normalisation is particularly important for our feature set, which combines dense BERT embeddings (768 dimensions per text field) with scalar metrics like word counts, entity counts, sentiment scores, and readability indices on very different scales.

The final feature set provides a rich representation of each paper, combining normalised semantic embeddings that capture complex meaning with interpretable metrics that quantify specific textual characteristics. The careful normalisation process ensures that all features contribute meaningfully to the classification task while maintaining relative relationships. The scaler object is preserved to enable consistent transformation of new data during model deployment.

# Experimentation (1st Run)

The initial experimental phase evaluated seven different model architectures on the original dataset to establish baseline performance metrics and identify promising approaches. The models ranged from simple linear classifiers to complex deep neural networks, allowing us to assess the relationship between model complexity and classification performance.

The experiments were conducted using a standardised training pipeline with consistent hyperparameters across models where applicable. All models were trained on the same feature set, including the BERT embeddings, word counts, entity counts, sentiment scores, and complexity metrics described in previous sections.

Each model was evaluated using stratified 5-fold cross-validation to ensure robust performance assessment across different data splits. The evaluation metrics include accuracy, precision, recall, and F1-score, calculated as weighted averages (accounting for class imbalance) and macro averages (treating all classes equally). This comprehensive evaluation framework allows for a detailed comparison of model performance across different aspects of the classification task.

The following table provides a comparative summary of the performance of all seven models evaluated in this study. The metrics include accuracy and weighted precision, recall, and F1-score averages.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
| M0: Logistic Regression (LogReg) | 0.69 | 0.81 (weighted)  0.47 (macro) | 0.69 (weighted)  0.64 (macro) | 0.73 (weighted)  0.49 (macro) |
| M1: Shallow Artificial Neural Network (ANN) | 0.70 | 0.82 (weighted)  0.48 (macro) | 0.70 (weighted)  0.67 (macro) | 0.73 (weighted)  0.50 (macro) |
| M2: Deep Artificial Neural Network (ANN) | 0.56 | 0.73 (weighted)  0.37 (macro) | 0.56 (weighted)  0.56 (macro) | 0.56 (weighted)  0.33 (macro) |
| M3: Recurrent Neural Network (RNN) | 0.66 | 0.81 (weighted)  0.46 (macro) | 0.66 (weighted)  0.63 (macro) | 0.70 (weighted)  0.46 (macro) |
| M4: Convolutional Neural Network (CNN) | 0.67 | 0.80 (weighted)  0.45 (macro) | 0.67 (weighted)  0.63 (macro) | 0.71 (weighted)  0.47 (macro) |
| M5: Autoencoder Neural Network (AENN) | 0.59 | 0.76 (weighted)  0.38 (macro) | 0.59 (weighted)  0.54 (macro) | 0.60 (weighted)  0.35 (macro) |
| M6: Residual Neural Network (ResNet) | 0.66 | 0.80 (weighted)  0.45 (macro) | 0.66 (weighted)  0.63 (macro) | 0.69 (weighted)  0.45 (macro) |

Figure 5: Comparative Summary of 1st Experimentation

The experimental results reveal several key patterns and insights:

**Model Performance Overview**

The shallow models (Logistic Regression and Shallow ANN) demonstrated surprisingly strong performance compared to their deeper counterparts. The Shallow Artificial Neural Network achieved the highest accuracy at 0.70, followed closely by Logistic Regression at 0.69. This suggests the classification task may not require deep architectural complexity to capture the underlying patterns.

**Deep Architecture Performance**

Interestingly, the Deep Artificial Neural Network (M2) performed the worst across all metrics, with an accuracy of only 0.56. This unexpected result might indicate potential overfitting or difficulties training the deeper architecture with the given dataset size and feature distribution. The other deep architectures (RNN, CNN, ResNet) performed moderately better but couldn't surpass the simpler models.

**Precision-Recall Trade-off**

All models showed higher weighted precision than their recall scores, suggesting a tendency to be more conservative in their predictions. The gap between precision and recall is particularly noticeable in the Logistic Regression (0.81 vs 0.69) and Shallow ANN (0.82 vs 0.70), indicating these models might be better at avoiding false positives at the cost of missing some positive cases.

**Macro vs Weighted Metrics**

The substantial difference between macro and weighted metrics (e.g., macro F1-scores around 0.45-0.50 vs weighted F1-scores around 0.70-0.73) indicates a significant class imbalance in the dataset. This suggests that models perform better on more prevalent classes but struggle with minority classes.

**Model Stability**

The CNN, RNN, and ResNet showed similar performance patterns (accuracies between 0.66-0.67), suggesting that the sequential or spatial features these architectures are designed to capture may not provide significant advantages for this classification task.

## Model Selection for Next Iteration

Based on the results from the first experimental run, we selected the top 3 performing models for further evaluation with a balanced dataset.

The Shallow Artificial Neural Network (M1) emerged as the best overall performer, with 0.70 accuracy. It also achieved the highest weighted precision (0.82) and strong F1 Score (0.73). This model demonstrated an excellent balance between architectural complexity and performance metrics, making it a prime candidate for further optimisation.

Logistic Regression (M0) proved to be a surprisingly strong contender, achieving 0.69 accuracy with strong weighted precision (0.81) and an F1 Score (0.73). As the simplest model in our evaluation, its competitive performance suggests that linear decision boundaries might be sufficient for significant portions of our classification task.

The Convolutional Neural Network (M4) showed moderate but promising performance, with 0.67 accuracy, good weighted precision (0.80), and an F1 Score (0.71). While RNN and ResNet achieved similar metrics, we selected the CNN for further evaluation due to its slightly better F1 score, faster training time, and lower computational requirements.

The selection criteria for these models encompassed multiple factors, including overall performance metrics (accuracy, precision, recall, F1-score), computational efficiency, model simplicity, interpretability, and potential for improvement with balanced data. By choosing a mix of simple (Logistic Regression), moderate (Shallow ANN), and complex (CNN) architectures, we aimed to provide a comprehensive evaluation framework for the balanced dataset phase of our experiment.

# Dataset Balancing and Preparation

After analysing the results from the first experimental phase, we identified class imbalance as a significant factor affecting model performance. To address this, we performed comprehensive dataset balancing using the preprocessing and feature engineering pipelines developed in our initial phase.

The data preprocessing pipeline included several key steps. First, we cleaned and normalised text, then lowercase all text fields. We removed special characters and numbers from the text, standardised the text encoding to UTF-8, and performed tokenising all text fields.

Following the preprocessing steps, we applied our feature engineering pipeline to extract meaningful features from the data. We generated BERT embeddings for the title, summary, comment, and author fields. We also calculated word count statistics and Named Entity Recognition (NER) counts. Additionally, we performed sentiment analysis to generate sentiment scores and computed text complexity metrics using ARI scores.

These preprocessing and feature engineering steps were carefully maintained from the first experimental phase to ensure consistency and comparability of results. The key difference in this phase was the implementation of balanced sampling to address the class distribution issues identified earlier.

The balanced dataset consisted of 21,152 observations, split into 13,264 training samples, 5,768 validation samples, and 2,120 test samples. Each category contained exactly 2,644 observations to ensure a balanced representation across classes.

We carefully balanced the dataset using random undersampling to ensure a fair comparison between models. This technique was chosen over oversampling methods to avoid potential overfitting that could arise from synthetic data generation. The balanced dataset contains 21,152 observations, with 2,644 samples per category, ensuring equal representation across all classes.

The dataset was split into training (62.7%), validation (27.3%), and test (10%) sets, maintaining the balanced class distribution across all splits. This resulted in 13,264 training samples, 5,768 validation samples, and 2,120 test samples. The split ratios were chosen to provide sufficient data for model training while retaining a substantial validation set for model selection and hyperparameter tuning.

The preprocessing pipeline remained consistent with the original dataset to maintain comparability of results. This included standardising numerical features, encoding categorical variables, and handling missing values. Feature engineering steps were also kept identical to ensure that performance improvements could be attributed to the balanced data rather than changes in the feature space.

The balanced dataset preparation phase was crucial for addressing the class imbalance issues identified in the first experimental run. By equalising the class distributions, we aimed to reduce bias towards majority classes and improve model performance on minority classes. This balancing also made macro and weighted metrics more directly comparable, allowing for a better assessment of model performance across all classes. Additionally, the balanced dataset provided a more reliable evaluation of each model's true discriminative capabilities by ensuring all classes were equally represented in the training data.

This balanced dataset was the foundation for our second experimental run, allowing us to evaluate whether the selected models could perform better when trained on equally represented classes.

# Experimentation (2nd Run)

In the second experimental run, we evaluated the balanced dataset’s three selected models (Logistic Regression, Shallow ANN, and CNN). This phase assessed whether addressing the class imbalance would improve model performance and produce more consistent results across classes.

From the first run, each model was trained using identical preprocessing and feature engineering pipelines, with the key difference being the balanced training data. We maintained consistent hyperparameter settings from the first experimental phase to isolate the effects of data balancing on model performance.

The balanced dataset provided equal representation across all classes, allowing us to better evaluate each model's true discriminative capabilities without the bias introduced by class imbalance. This setup also enabled more meaningful comparisons between macro and weighted metrics, as the balanced class distribution meant these metrics should theoretically converge.

The following table provides a comparative summary of the performance of all seven models evaluated in this study. The metrics include accuracy and weighted precision, recall, and F1-score averages.

| **Model** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
| --- | --- | --- | --- | --- |
| M7: Logistic Regression (LogReg) | 0.71 | 0.71 (weighted & macro) | 0.71 (weighted & macro) | 0.69 (weighted & macro) |
| M8: Shallow Artificial Neural Network (ANN) | 0.76 | 0.76 (weighted & macro) | 0.76 (weighted & macro) | 0.76 (weighted & macro) |
| M9: Convolutional Neural Network (CNN) | 0.74 | 0.74 (weighted & macro) | 0.74 (weighted & macro) | 0.74 (weighted & macro) |

Figure 6: Comparative Summary of 2nd Experimentation

The experimental results reveal several key patterns and insights.

The second experimental run with balanced data revealed significant improvements across all models compared to the first run. Most notably, the Shallow Artificial Neural Network (M8) demonstrated exceptional performance with 0.76 accuracy across all metrics (weighted and macro), substantially improving from its previous 0.70 accuracy. This consistent performance across both weighted and macro metrics indicates that the model performs equally well across all classes, validating the effectiveness of our data-balancing approach.

The Convolutional Neural Network (M9) also showed marked improvement, achieving 0.74 accuracy (up from 0.67) and consistent performance across all metrics. This improvement suggests that the class imbalance previously hindered CNN's ability to capture spatial patterns in the data, and the balanced dataset allowed it to learn discriminative features better for all classes.

Logistic Regression (M7) maintained its strong performance with 0.71 accuracy (slightly higher than its previous 0.69), demonstrating remarkable resilience and consistency across imbalanced and balanced datasets. The model's weighted and macro metrics are nearly identical (around 0.71 for precision and recall, 0.69 for F1-score), indicating uniform performance across all classes. This suggests that the linear decision boundaries it creates are equally effective for all categories in the balanced scenario.

A particularly interesting observation is the convergence of weighted and macro metrics for all models in this balanced dataset scenario. This convergence confirms that our data balancing strategy successfully eliminated the bias towards majority classes present in the first run. The consistent performance across both metric types indicates that all models are now making equally reliable predictions across all classes rather than achieving higher performance on majority classes at the expense of minority classes.

# Experimentation (3rd Run)

Building upon the insights gained from the second experimental run, we conducted a third phase focused on optimising the neural network architecture through extensive hyperparameter tuning. This phase aimed to identify the optimal model configuration that could improve the strong performance achieved with the balanced dataset.

The hyperparameter search focused on two critical aspects of neural network design: the hidden layer dimensions and learning rates. These parameters were chosen for optimisation as they significantly impact the model's capacity to learn complex patterns and training dynamics. By conducting a comprehensive grid search across these parameters, we aimed to find the configuration that would maximise the model's discriminative power while maintaining stable training.

This experimental phase maintained the same balanced dataset and preprocessing pipeline from the second run to ensure valid comparisons. The key difference was systematically exploring the hyperparameter space to find the optimal model architecture.

We conducted an extensive hyperparameter search for the third experimental run to optimise the neural network architecture. We explored a wide range of hidden layer dimensions, from very small (2 neurons) to very large (2,056 neurons), allowing us to understand how the model's capacity affects its performance. The hidden dimensions tested were 2, 4, 8, 16, 32, 64, 128, 256, 512, 1,024, and 2,056 neurons.

Additionally, we investigated the impact of different learning rates, spanning seven orders of magnitude from 1e-7 to 1e-1. This broad range enabled us to find the spot between convergence speed and stability. The learning rates tested were 1e-1, 1e-2, 1e-3, 1e-4, 1e-5, 1e-6, and 1e-7.

The hyperparameter search was performed using validation loss as the primary metric for model selection. Each hidden dimension and learning rate combination was evaluated, resulting in 77 different model configurations. The models were trained using the same balanced dataset from the second experimental run to maintain consistency and comparability.

The hyperparameter optimisation process revealed several key insights about the neural network architecture. The best-performing model utilised a hidden dimension of 256 neurons with a learning rate 0.001, achieving a validation loss of 1.5293. This configuration represents a balance between model complexity and training stability.

The results show that larger hidden dimensions (1024, 2056) generally performed worse, especially with higher learning rates (0.1, 0.01), often resulting in validation losses above 2.0. This suggests that overly complex architectures may be prone to overfitting on this particular dataset. Similarly, very small hidden dimensions (2, 4, 8) struggled to capture the underlying patterns in the data, particularly with lower learning rates.

The learning rate proved to be a crucial factor in model performance. Very high learning rates (0.1) consistently led to poor validation losses across different hidden dimensions, while very low learning rates (1e-07) resulted in slow convergence and suboptimal performance. The optimal learning rate of 0.001 provided the right balance for effective training.

| **Model** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
| --- | --- | --- | --- | --- |
| M8: Shallow Artificial Neural Network (ANN) | 0.76 | 0.76 (weighted & macro) | 0.76 (weighted & macro) | 0.76 (weighted & macro) |
| M10: Hyperparameter Optimised (ANN) | 0.77 | 0.77 (weighted & macro) | 0.77 (weighted & macro) | 0.77 (weighted & macro) |

Figure 7: Comparative Summary of 3rd Experimentation

The evaluation results reveal several interesting patterns when comparing the baseline shallow neural network (M₈) With its hyperparameter-optimized counterpart (M₁₀). Most notably, the optimised model demonstrates consistent Improvement across all evaluation metrics, albeit with modest gains.

The hyperparameter-optimized model achieves 77% accuracy, representing a one-point improvement over the baseline model's 76%. This pattern of improvement is mirrored across all metrics, with both weighted and macro-averaged precision, recall, and F1 Scores showing similar one-point gains. The consistency of this improvement across different metrics suggests that the optimisation process led to genuine, albeit incremental, enhancement in model performance rather than just improvements in specific areas.

An interesting observation is the identical values between weighted and macro-averaged metrics for both models. This suggests a relatively balanced performance across different classes, as significant class imbalances would typically result in disparities between weighted and macro-averaged metrics. This balance is maintained even after hyperparameter optimisation, indicating that the tuning process did not introduce bias toward any particular class.

While the improvements are modest, they demonstrate the value of hyperparameter optimisation in fine-tuning model performance. The consistent nature of these improvements across all metrics suggests that the optimised model is more robust and reliable than its baseline counterpart, even if the gains are not dramatic.

# Key Findings

The analysis and experimentation conducted in this study revealed several key findings.

The optimisation of the model architecture revealed that a hidden dimension of 256 neurons provided the best performance, effectively balancing model complexity and effectiveness. Larger architectures with 1024 or more neurons showed diminishing returns and potential overfitting issues, while very small architectures with fewer than eight neurons lacked sufficient capacity to model the relationships in the data properly.

The learning rate proved to be a highly sensitive parameter in the training process. An optimal learning rate of 0.001 was crucial for model performance. Higher learning rates of around 0.1 consistently led to unstable training across all tested architectures. Conversely, very low learning rates at 1e-07 resulted in slow convergence and suboptimal performance outcomes.

The hyperparameter-optimized model consistently improved across all evaluation metrics. Compared to the baseline model, its accuracy increased from 76% to 77%. Both weighted and macro-averaged metrics showed uniform improvements, indicating balanced performance across all classes in the dataset.

The class balance analysis revealed identical weighted and macro-averaged metrics, suggesting well-balanced performance across different classes. This balance was maintained throughout the optimisation process, demonstrating robust and unbiased model behaviour.

While the improvements from optimisation were modest in magnitude, they were notably consistent across all evaluation metrics. Optimisation resulted in a more reliable and robust model without introducing class-specific biases. These results demonstrate the value of systematic hyperparameter tuning, even when the resulting gains are incremental.

These findings highlight the importance of careful model architecture design and hyperparameter selection in neural network development. They also demonstrate that even modest improvements through optimisation can lead to more robust and reliable models.

# Future Work

Several promising directions for future work emerge from this study. First, exploring more sophisticated neural network architectures, such as deep neural networks with multiple hidden layers or architectures incorporating residual connections, could capture more complex patterns in the data. This could help overcome the current model's performance ceiling and achieve more substantial improvements over the baseline.

Investigating alternative optimisation techniques, such as adaptive learning rate methods like Adam or RMSprop, could provide better training dynamics than the current approach. Additionally, implementing batch normalisation or dropout techniques could enhance model regularisation and improve generalisation performance.

Another valuable direction would be to conduct a more extensive feature engineering process. While the current model works with the existing feature set, developing domain-specific features or applying advanced feature selection methods might uncover more informative patterns in the data. This could include exploring feature interactions or incorporating domain knowledge to create more meaningful representations.

Expanding the hyperparameter search space could also yield valuable insights. While this study focused on hidden dimensions and learning rates, other parameters such as batch size, activation functions, and optimisation algorithms could be included in the optimisation process. A more comprehensive grid search or the implementation of advanced hyperparameter techniques like Bayesian optimisation could potentially discover better model configurations.

Finally, investigating the model's behaviour on different subsets of the data or specific edge cases could provide insights into its limitations and guide future improvements. This could include analysing misclassified examples in detail or evaluating the model's performance in particularly challenging instances. Such analysis could inform targeted improvements to the model architecture or training process.

# Acknowledgements

We want to express our sincere gratitude to Professor Jin Cheon Na for his invaluable guidance and support throughout this research project. His expertise and insightful feedback have significantly improved this work.

# Appendix I – N-Gram Analysis

N-gram analysis provides deeper insights into how words are commonly used together in scientific texts across different fields. By examining frequent word combinations (2-grams, 3-grams, and 4-grams), we can better understand each discipline's key concepts, methodologies, and research focuses. This analysis reveals common phrases and terminology that characterise the discourse in each field. Below, we present the most frequent n-grams for each scientific category, starting with Physics.

## Physics

The n-gram analysis of physics papers reveals interesting patterns in the language and focus of physics research. Looking at the 3-grams, we see a strong emphasis on experimental physics and astronomical observations, with phrases like "hubble space telescope" and references to specific measurement techniques. The "van der waals" frequency indicates significant research activity in molecular forces and interactions.

The 4-gram analysis provides deeper insights into physics papers' methodological and topical focus. The most frequent 4-gram "et al phys rev" and "al phys rev lett" reflect the dominance of Physical Review journals in physics publications. There's a notable presence of astronomy-related terms like "sloan digital sky survey" and "cosmic microwave background cmb", indicating the field's strong astronomical research component. Methodological approaches are represented by phrases like "density matrix renormalization group" and "markov chain monte carlo", showing the importance of computational and theoretical methods. "density functional theory dft" suggests significant activity in quantum mechanics and materials science.

The 5-gram analysis further reinforces these patterns while revealing additional details about research practices. Publication-related phrases dominate, with "et al phys rev lett" being the most frequent. Technical methodologies are elaborated in phrases like "density matrix renormalization group dmrg" and "using density matrix renormalization group". Experimental physics is represented by phrases related to particle physics facilities like "relativistic heavy ion collider rhic". The presence of phrases about statistical error reporting ("first error statistical second systematic") indicates the field's rigorous approach to experimental uncertainty.

This n-gram analysis reveals physics as a field balanced between theoretical frameworks, experimental methodologies, and observational astronomy. It strongly emphasises rigorous publication practices and statistical analysis.

## Mathematics

The n-gram analysis of Mathematics papers reveals interesting patterns in the language and concepts commonly used in mathematical research. Looking at the 3-grams, we see a strong emphasis on boundary value problems and algebraic concepts like vertex operator algebra and Lie groups, reflecting core areas of mathematical research.

The 4-gram analysis provides deeper insights into the mathematical discourse patterns. The most frequent 4-gram "give necessary sufficient conditions" (46 occurrences) indicates the formal nature of mathematical proofs and theorem statements. There's also a significant presence of algebraic terminology with phrases like "algebraically closed field characteristic" (29 occurrences) and "let g finite group" (20 occurrences). The analysis reveals frequent discussion of various mathematical domains, including differential equations (both partial and ordinary), topology (through phrases involving "compact Hausdorff space"), and group theory (references to "locally compact group").

The 5-gram analysis further reinforces these patterns while revealing more specific mathematical constructs. The presence of "algebraically closed field characteristic zero" and related variants suggests substantial work in abstract algebra and field theory. The phrase "modules finite dimensional weight spaces" indicates research in representation theory, while "alternating direction method multipliers admm" points to applications in optimisation theory. The analysis also shows frequent discussion of categorical concepts through phrases like "bounded derived categories coherent sheaves" and geometric concepts via "smooth projective curve."

Overall, the n-gram analysis effectively captures the formal, precise nature of mathematical writing while highlighting the predominant subfields and methodological approaches in mathematics research. The frequent occurrence of phrases related to conditions, proofs, and specific mathematical structures aligns well with mathematical discourse’s theoretical and rigorous nature.

## Electrical Engineering and Systems Science

The n-gram analysis of the Electrical Engineering and Systems Science papers reveals several key research areas and methodological approaches that are dominant in the field. Looking at the 4-grams, we see a strong focus on speech recognition and neural networks, with "automatic speech recognition asr" being the most frequent (32 occurrences), followed by "model predictive control mpc" and "convolutional neural network cnn" (14 occurrences each). This suggests that speech processing and neural network applications are major research areas within electrical engineering.

The prevalence of terms related to deep learning and neural networks is particularly notable, with multiple variations appearing in the top 20 list: "convolutional neural networks cnns", "deep neural network dnn", and "deep neural networks dnns". This indicates the significant role of deep learning methodologies in current electrical engineering research. Additionally, the presence of terms like "sound event detection sed" and "automatic speaker verification asv" further emphasises the field's strong focus on audio processing and recognition systems.

The 5-gram analysis provides more detailed insights into specific methodological approaches and applications. The most frequent 5-gram, "minimum variance distortionless response mvdr" (5 occurrences) is a key technique in signal processing. The strong presence of speech recognition-related 5-grams, such as "automatic speech recognition asr systems" and variations thereof, reinforces the field's emphasis on speech processing technologies. The appearance of terms like "massive multipleinput multipleoutput mimo systems" and "wireless information power transfer swipt" highlights the importance of wireless communication systems in the field.

Notably, both 4-gram and 5-gram analyses significantly focus on experimental and simulation results, with phrases like "simulation results show proposed" and "experimental results show proposed" appearing frequently. This strongly emphasises empirical validation and practical applications in electrical engineering research. The presence of various performance metrics (like "word error rate wer" and "bit error rate ber") further underscores the field's focus on quantitative evaluation and performance optimisation.

## Computer Science

The n-gram analysis of computer science abstracts reveals interesting patterns in the field's terminology and research focus areas. Looking at the 3-grams, we strongly emphasise neural networks and language models, with terms like "channel state information" and "recurrent neural network" appearing frequently. This suggests a significant focus on machine learning and natural language processing research.

The 4-gram analysis further reinforces this observation, with "large language models llms" being the most frequent 4-gram, followed by various neural network architectures like "convolutional neural network cnn" and "deep neural networks dnns". There's also a notable presence of reinforcement learning ("multiagent reinforcement learning marl") and natural language processing ("natural language processing nlp"). The frequency of terms related to experimental results ("experimental results show proposed", "experimental results demonstrate proposed") indicates a strong empirical focus in computer science research.

The 5-gram analysis shows various technical concepts spanning multiple computer science subfields. While some terms continue the machine learning theme ("deep convolutional neural networks cnns"), others relate to theoretical computer science ("theory practice logic programming tplp"), wireless communications ("additive white gaussian noise awgn"), and emerging technologies ("central bank digital currency cbdc"). The presence of statistical and mathematical terms ("minimum mean square error mmse", "markov chain monte carlo mcmc") demonstrates the quantitative foundation of computer science research.

This n-gram analysis effectively captures the multifaceted nature of computer science research. It highlights its strong focus on machine learning and AI while showing its breadth across theoretical, practical, and emerging technological domains.

## Quantitative Biology

The n-gram analysis of quantitative biology papers reveals distinct patterns that highlight the field's focus on biological systems, mathematical modelling, and medical applications. Looking at the 4-grams, we observe a strong emphasis on epidemiological research, with phrases like "basic reproduction number r" and "severe acute respiratory syndrome" frequently appearing, likely reflecting significant research activity related to infectious diseases and epidemics.

The analysis substantially focuses on computational and statistical methods applied to biological problems. Terms like "roc curve auc cstatistic" and "approximate bayesian computation abc" indicate the importance of statistical analysis and model evaluation in the field. The presence of "partial differential equation pde" and "ordinary differential equations odes" demonstrates the field's reliance on mathematical modelling approaches to understand biological systems.

Molecular and genetic research themes are evident through phrases like "transcription factor binding sites", "single nucleotide polymorphisms snps", and "gene regulatory networks grns". This indicates significant research activity in genomics and gene regulation. The appearance of "molecular dynamics md simulations" and "intrinsically disordered proteins idps" suggests active protein structure and dynamics research.

Neurobiological research is represented by terms like "functional magnetic resonance imaging" and "slow wave sleep duration," indicating its involvement in brain research and sleep studies. The presence of "protein interaction networks" and "model gene regulatory networks" highlights the importance of network analysis approaches in understanding biological systems.

The diversity of these n-grams reflects quantitative biology's interdisciplinary nature, combining biological research with mathematical modelling, statistical analysis, and computational methods. The field appears to span multiple scales of biological organisation, from molecular interactions to whole-organism studies and population-level analyses.

## Economics

The n-gram analysis of Economics papers reveals several interesting patterns in the field’s research focus and methodological approaches. Looking at the 4-grams, there is a notable emphasis on financial risk and stock market dynamics, with phrases like "risk stock price crashes" appearing frequently. This suggests a significant research interest in market volatility and financial crashes within the economics literature.

Game theory and equilibrium analysis also feature prominently, as evidenced by phrases such as "pure strategy nash equilibria" and "optimum pure strategy nash". This indicates the importance of game theoretical frameworks in economic research, particularly in studying strategic interactions and decision-making processes.

The data also focuses on green technology and innovation, with multiple related 4-grams, including "green technological innovation risk" and "technological innovation risk stock". This suggests growing attention to environmental economics and the intersection of sustainability with financial markets.

The 5-gram analysis further reinforces these themes while providing additional context. The prevalence of phrases related to news media and company reporting (e.g., "negative news reports media listed") indicates research interest in how information flow affects economic outcomes. Infrastructure and development economics also appear to be important themes, as shown by phrases like "impact electricity blackouts poor infrastructure" and "electricity blackouts poor infrastructure livelihood".

Methodological approaches are also evident in the n-grams, with phrases like "twoway fixed effects estimator" and "extended twoway fixed effects" suggesting the use of sophisticated econometric techniques in empirical research. The terms related to discrete choice models and value distribution indicate a strong quantitative and empirical orientation in economic research methodologies.

## Statistics

The n-gram analysis of Statistics papers reveals several key methodological and analytical themes that dominate the field. Looking at the 4-grams, Markov Chain Monte Carlo (MCMC) emerges as the most prevalent technique, with 86 occurrences of "markov chain monte carlo" and 33 occurrences of "chain monte carlo mcmc". This highlights the importance of MCMC methods in statistical computation and Bayesian inference.

Other significant methodological approaches include Approximate Bayesian Computation (ABC) and Sequential Monte Carlo (SMC), which appear 10 and 9 times, respectively. The presence of "principal component analysis pca" and "reproducing kernel hilbert space" (6 occurrences each) indicates the relevance of dimensionality reduction techniques and functional analysis in statistical research.

The 5-gram analysis further reinforces the prominence of MCMC methods, with variations like "markov chain monte carlo mcmc" (33 occurrences) and "using markov chain monte carlo" (7 occurrences) appearing frequently. The analysis also emphasises practical applications and validation, with phrases like "extensive simulation studies real data" and "simulation studies real data analysis" appearing multiple times.

Notably, there's a significant focus on hierarchical modelling and Bayesian methodology, as evidenced by phrases like "bayesian checking second levels hierarchical" and "checking second levels hierarchical models." The presence of "integrated nested laplace approximation inla" suggests the use of advanced computational methods for Bayesian inference, particularly in complex statistical models.

## Quantitative Finance

The n-gram analysis of Quantitative Finance papers reveals interesting patterns in the research focus and methodologies within this field. Looking at the 4-grams, we see a strong emphasis on computational and statistical methods, with "markov chain monte carlo" being the most frequent (7 occurrences). This highlights the importance of stochastic modelling in financial research. The prominence of "limit order book lob" and related terms (5 occurrences) indicates significant research attention to market microstructure and order book dynamics.

The analysis also focuses on fundamental financial concepts, with "fundamental theorem asset pricing" appearing frequently (5 occurrences). Machine learning and artificial intelligence approaches are well-represented, as evidenced by terms like "long shortterm memory lstm" and "deep deterministic policy gradient", suggesting the growing integration of advanced computational methods in quantitative finance research.

Examining the 5-grams provides more detailed insights into specific research areas. Market microstructure remains a key theme, with "limit order book lob data" appearing frequently (3 occurrences). There's notable attention to specific market analysis, particularly regarding the Shenzhen Stock Exchange, as indicated by several related 5-grams. Risk management and volatility modelling are prominent themes, shown by phrases like "risk measures valueatrisk expected shortfall" and "local stochastic volatility lsv models".

The presence of terms related to deep reinforcement learning and behavioural analysis suggests an emerging focus on advanced algorithmic trading strategies and market behaviour studies. Additionally, the appearance of agricultural commodity-related terms ("wheat maize soyabeans rice") indicates research interest in commodity markets and their dynamics.

# Appendix II – Topic Modelling

The topic modelling analysis for Quantitative Finance reveals several distinct research themes and methodological approaches within the field. Using Latent Dirichlet Allocation (LDA), we identified five main topics from the paper summaries, each representing different aspects of quantitative finance research. The analysis provides insights into the current research focus areas, methodological preferences, and emerging trends in the field. Below are the detailed findings for each topic and their relative prevalence in the corpus.

## Physics

The topic modelling analysis for Physics reveals distinct research areas and methodological approaches. Topic 1, with keywords like "model", "phase", "field", "theory", and "quantum", appears to represent theoretical physics research, particularly quantum mechanics and field theories. This topic has the highest document count (10,379), suggesting it's a dominant area of research. Topic 2 focuses on classical physics and astrophysics, with terms like "mass", "velocity", "gas", and "density", indicating research related to fluid dynamics and celestial body formation (2,730 documents). Topic 3 is centred on observational astronomy and astrophysics, featuring terms like "emission", "galaxies", "observations", and "stars", with 2,920 documents discussing these themes.

Topic 4, with 5,191 documents, appears to concentrate on experimental physics, particularly in areas involving particle physics and electromagnetic phenomena, as evidenced by terms like "energy," "magnetic," "beam," and "electron." Topic 5, with 5,454 documents, represents an intersection of quantum physics and modern computational methods. Terms like "quantum," "systems," "network," and "networks" suggest research in quantum computing or complex systems.

The distribution of documents across these topics indicates a relatively balanced research landscape in physics, with theoretical physics (Topic 1) having the largest share, followed by computational/quantum systems (Topic 5) and experimental physics (Topic 4), while classical physics/astrophysics (Topic 2) and observational astronomy (Topic 3) have somewhat smaller but still significant representation. This distribution reflects the modern state of physics research, where theoretical and computational approaches are highly prevalent while maintaining strong experimental and observational components.

## Mathematics

The topic of modelling analysis for Mathematics reveals distinct research areas and methodological approaches. Topic 1, with keywords like "problem," "method," "equation," and "solution," appears to represent applied mathematics and numerical analysis, focusing on problem-solving and mathematical modelling (3,200 documents). This topic emphasises the practical and computational aspects of mathematics.

Topic 2 (1,908 documents) centres on abstract algebra and number theory, as evidenced by terms like "ring", "number", "theorem", and "ideal". The presence of "proof" and "prove" indicates the rigorous theoretical nature of this research area, highlighting the fundamental role of mathematical proofs in establishing new results.

Topic 3, with 2,603 documents, focuses on analysis and topology. It features terms like "space," "spaces," "compact," and "metric." This topic represents research in functional analysis, metric spaces, and related theoretical frameworks that form the foundation for many branches of modern mathematics.

Topic 4 is the largest (3,541 documents) and concentrates on algebraic structures and category theory. Keywords include "group," "algebra," "category," and "lie." This suggests a strong research focus on abstract algebraic systems and their theoretical foundations, particularly in group theory and Lie algebras.

Topic 5 (2,542 documents) appears to focus on geometric and topological aspects of mathematics, using terms like "graph," "manifolds," "surfaces," and "curves." This topic represents research in geometric topology, graph theory, and differential geometry, highlighting the spatial and structural aspects of mathematical research.

The distribution of documents across these topics shows a relatively balanced research landscape in mathematics, with a slight emphasis on algebraic structures (Topic 4) and applied mathematics (Topic 1). The presence of proof-related terms across multiple topics underscores the fundamental importance of mathematical rigour and formal demonstration in all areas of mathematical research. This distribution reflects the modern state of mathematics, where theoretical foundations continue to be developed alongside practical applications and computational methods.

## Electrical Engineering and Systems Science

The topic modelling analysis for Electrical Engineering and Systems Science reveals distinct research areas and methodological approaches. Topic 1, with keywords like "control", "power", "energy", and "systems", appears to focus on power systems and control engineering (193 documents). This topic emphasises the practical applications of electrical engineering in power management and control systems design.

Topic 2, with the largest document count (289), centres on systems engineering and methodological approaches, as evidenced by terms like "systems", "method", "approach", and "using". The frequent appearance of "proposed" suggests a strong focus on novel methodological contributions in this area.

Topic 3 (140 documents) concentrates on signal processing and detection systems, particularly in speech processing, as indicated by keywords like "detection", "noise", and "speech". This topic represents research in signal detection, noise reduction, and speech processing technologies.

Topic 4 emerges as the dominant topic, with 511 documents. It focuses on machine learning and computer vision applications, and keywords include "speech," "image," "data," "network," and "models." This suggests a significant research emphasis on deep learning applications in speech and image processing.

Topic 5 (204 documents) appears to focus on communications engineering. Terms like "channel," "communication," "wireless," and "performance" indicate research in wireless communications and network systems. The presence of "algorithm" and "performance" strongly emphasises optimisation and system performance evaluation.

Document distribution across these topics clearly emphasises machine learning and computer vision applications (Topic 4), followed by systems engineering methodologies (Topic 2). The relatively smaller representation in signal processing (Topic 3) and power systems (Topic 1) suggests more specialised research areas might exist. This distribution reflects the modern state of electrical engineering and systems science, where data-driven approaches and machine-learning applications have become increasingly prominent.

## Computer Science

The topic modelling analysis for Computer Science reveals distinct research areas and methodological approaches. Topic 1, with keywords like "systems", "design", "performance", and "software", appears to focus on systems and software engineering (3,321 documents). This topic emphasises the practical aspects of computer science, particularly in system design and implementation.

Topic 2 (2,779 documents) centres on the theoretical and mathematical aspects of computer science, as evidenced by terms like "model," "problem," "linear," and "method." The presence of "channel" suggests applications in communication systems, while the combination of modelling terms indicates a focus on mathematical modelling and problem-solving approaches.

Topic 3, comprising 2,162 documents, focuses on algorithms and graph theory, featuring terms like "algorithm", "algorithms", "graph", and "graphs". This topic represents core computer science research in algorithmic design and analysis, particularly in graph-based problems and network algorithms.

Topic 4 emerges as a distinct topic (1,832 documents) concentrating on social computing and user interaction. Keywords include "data," "information," "users," and "social." This suggests a significant research focus on human-computer interaction, social media analysis, and user behaviour studies.

Topic 5 (2,586 documents) represents machine learning and neural networks, using terms like "learning," "neural," "models," and "method." This topic reflects the growing importance of artificial intelligence and machine learning in modern computer science research, emphasising neural network architectures and learning methodologies.

The distribution of documents across these topics shows a balanced research landscape in computer science, with a slight emphasis on systems and software engineering (Topic 1). The significant presence of machine learning (Topic 5) and theoretical computer science (Topic 2) reflects the field's current trends. The relatively smaller representation in social computing (Topic 4) suggests this might be a more specialised research area. This distribution effectively captures the diverse nature of modern computer science, spanning from theoretical foundations to practical applications and emerging technologies.

## Quantitative Biology

The topic modelling analysis for Quantitative Biology reveals distinct research areas and methodological approaches within the field. Topic 1, with keywords like "protein", "proteins", "cell", and "structure", focuses on molecular and cellular biology (386 documents). This topic emphasises protein structure, dynamics, and folding, suggesting a strong focus on molecular biophysics and structural biology.

Topic 2 (289 documents) represents a diverse research area combining molecular biology and neuroscience, as evidenced by terms like "dna", "neurons", and "properties". The presence of modeling-related terms suggests this topic encompasses computational approaches to studying biological systems at both molecular and cellular levels.

Topic 3, comprising 479 documents, concentrates on computational neuroscience and network analysis. Keywords include "brain," "networks," and "learning." This topic reflects the growing importance of data-driven approaches and machine learning in understanding neural systems and brain function.

Topic 4 emerges as the largest topic (525 documents), focusing on ecological and evolutionary biology, with terms like "species", "population", "evolution", and "growth". The presence of "network" and "dynamics" suggests an emphasis on studying complex biological systems and their interactions at population and ecosystem levels.

Topic 5 (182 documents) appears to focus on genomics and phylogenetics, particularly in cancer research, as indicated by keywords like "cancer", "tree", "genes", and "species". This topic represents the intersection of molecular biology with evolutionary analysis, particularly in the context of disease studies.

The distribution of documents across these topics shows a balanced research landscape in quantitative biology, with a slightly higher emphasis on ecological/evolutionary biology (Topic 4) and computational neuroscience (Topic 3). The smaller representation in cancer genomics (Topic 5) suggests this might be a more specialised research area. This distribution reflects the modern state of quantitative biology, where computational and mathematical approaches are applied across different scales of biological organisation, from molecular to ecosystem levels.

## Economics

The topic modelling analysis for Economics reveals distinct research areas and methodological approaches. Topic 1 (46 documents) focuses on empirical economic analysis, particularly in the energy and utility sectors, with keywords like "electricity," "demand," and "energy." The presence of "effects" and "treatment" suggests an emphasis on causal analysis and impact evaluation studies.

Topic 2 (50 documents) represents theoretical economic research on equilibrium modelling and agent-based approaches. Keywords like "equilibrium", "agents", and "choice" indicate a focus on microeconomic theory and decision-making models, with network effects also being a significant consideration.

Topic 3, comprising 68 documents, focuses on macroeconomic policy and cross-country analysis. The combination of terms like "countries", "policy", and "economic" suggests research examining economic policies and their performance across different nations, supported by empirical data analysis.

Topic 4 is the largest (104 documents), concentrating on econometric methods and statistical analysis. Keywords such as "model," "data," "treatment," and "distribution" indicate a strong focus on quantitative research methods and statistical testing in economic analysis.

Topic 5 (40 documents) represents research on economic growth and complex systems. Terms like "growth," "network," "complexity," and "GDP " suggest studies of economic development and interconnected economic systems. The unexpected presence of "quantum" might indicate interdisciplinary research or a methodological crossover from physics.

The distribution of documents across these topics clearly emphasises quantitative methods and empirical analysis (Topic 4), followed by policy research (Topic 3). The relatively smaller representation in growth and complexity studies (Topic 5) suggests this might be a more specialised research area. This distribution reflects the modern state of economics research, which balances theoretical frameworks with empirical analysis and policy applications.

## Statistics

The topic modelling analysis for Statistics reveals several distinct research areas and methodological approaches. Topic 1 (280 documents) represents a broad focus on statistical modelling with a Bayesian emphasis, as indicated by keywords like "data", "model", and "bayesian". This topic suggests research combining theoretical frameworks with practical applications using various methodological approaches.

Topic 2 (326 documents) concentrates on computational statistics and sampling methods, particularly Monte Carlo techniques. Keywords like "algorithm", "carlo", "monte", and "sampling" indicate a strong focus on computational approaches to statistical problems, with Bayesian methods also playing a significant role.

Topic 3 (93 documents) focuses on advanced statistical learning methods, particularly kernel-based approaches. The presence of terms like "kernel", "learning", and "statistical" suggests research at the intersection of statistics and machine learning, emphasising methodological developments.

Topic 4 (200 documents) covers traditional statistical analysis and inference, focusing on temporal and spatial applications. Keywords such as "statistical," "inference," "time," and "spatial" indicate research involving various types of statistical analysis across different domains.

Topic 5 is the largest (442 documents), focusing on statistical methodology and estimation techniques. Terms like "estimation", "regression", and "proposed" suggest an emphasis on developing and applying statistical methods, particularly in the context of regression analysis and model estimation.

The document distribution across these topics strongly emphasises methodological development (Topic 5) and computational approaches (Topic 2). The relatively smaller representation in kernel-based methods (Topic 3) suggests this might be a more specialised research area. This distribution reflects the modern statistics state, balancing theoretical developments with computational methods and practical applications.

## Quantitative Finance

The topic modelling analysis for Quantitative Finance reveals distinct research areas within the field. Topic 1 (253 documents) focuses on market analysis and trading, with keywords like "market", "stock", "price", and "trading", indicating research on stock markets and trading behaviour. The presence of "learning" suggests applying machine learning techniques to financial market analysis.

Topic 2 (271 documents) concentrates on financial modelling, particularly derivatives and risk analysis. Keywords such as "volatility," "pricing," "stochastic," and "option" refer to research in option pricing models and stochastic processes, which represent the mathematical foundations of quantitative finance.

Topic 3 (125 documents) represents research in portfolio management and market equilibrium. Terms like "portfolio", "equilibrium", and "strategies" suggest studies focusing on portfolio optimisation, market equilibrium models, and investment strategies, bridging theoretical finance with practical applications.

Topic 4 (79 documents) focuses on broader economic and market risk analysis. The combination of terms like "trade", "countries", "economic", and "network" indicates research examining international trade, market networks, and firm-level analysis, with an emphasis on risk assessment.

Topic 5 (93 documents) emphasises financial modelling and risk analysis, focusing on statistical approaches. Keywords such as "distribution," "variables," and "wealth" suggest research involving statistical modelling of financial phenomena and wealth distribution, combining quantitative methods with financial applications.

The distribution of documents across these topics primarily focuses on financial modelling (Topic 2) and market analysis (Topic 1), which account for most papers. The smaller representation in international trade and network analysis (Topic 4) suggests this might be a more specialised research area. This distribution reflects the field's emphasis on mathematical modelling and market analysis while maintaining broader economic and strategic considerations coverage.

# Appendix III – Named Entity Recognition

The Named Entity Recognition (NER) analysis across different scientific fields reveals distinct patterns in how various entities are used in research papers. This analysis helps understand how disciplines reference and discuss entities like numbers, organisations, people, and concepts. By examining the most commonly named entities in each field, we can gain insights into the writing styles, methodological approaches, and key focus areas that define different academic disciplines.

The following sections present detailed NER analyses for Physics and Mathematics, highlighting the similarities and unique characteristics of how these fields use different types of entities in their research communications. This analysis provides an interesting lens to understand the linguistic and conceptual frameworks that shape scientific discourse in these fields.

## Physics

The Named Entity Recognition analysis for the Physics corpus reveals interesting patterns in the types of entities mentioned in physics research papers. The most frequent entities are predominantly numerical indicators, with cardinal and ordinal numbers dominating the top entities.

Cardinal numbers feature prominently, with "two" being the most frequent (7,192 occurrences), followed by "one" (3,437 occurrences), "three" (2,042 occurrences), "zero" (932 occurrences), "four" (825 occurrences), and "five" (284 occurrences). This high frequency of cardinal numbers reflects the quantitative nature of physics research, where numerical values and quantities play a crucial role in describing phenomena, measurements, and results.

Ordinal numbers also appear frequently, with "first" (3,544 occurrences), "second" (1,467 occurrences), and "third" (372 occurrences) being common. These ordinal numbers likely indicate sequential processes, ordered relationships, or prioritisation in physics research methodologies and findings.

Interestingly, "linear" appears as the only organisational entity (ORG) in the top 10, with 753 occurrences. This could reflect the importance of linear systems, linear algebra, or linear relationships in physics research, though its classification as an organisational entity might warrant further investigation.

The dominance of numerical entities in the physics corpus aligns with the field's mathematical and quantitative nature. The relative scarcity of other entity types (persons, locations, or dates) in the top entities suggests that physics research papers focus more on abstract concepts and numerical relationships rather than specific people, places, or temporal references.

## Mathematics

The Named Entity Recognition analysis for the Mathematics corpus shows similar patterns to Physics, with numerical entities dominating the most frequent occurrences. However, there are some notable differences in distribution and the presence of field-specific terms.

Cardinal numbers remain prominent, with "two" being the most frequent (2,703 occurrences), followed by "one" (1,595 occurrences), "three" (613 occurrences), "zero" (585 occurrences), and "four" (206 occurrences). While the pattern of cardinal numbers is similar to the Physics corpus, the frequencies are notably lower, possibly reflecting a smaller corpus size or different writing patterns in mathematical research.

Ordinal numbers also feature significantly, with "first" (1,480 occurrences), "second" (861 occurrences), and "third" (154 occurrences) appearing frequently. These ordinal numbers likely indicate sequential proofs, theorem statements, or ordered mathematical relationships, which are fundamental to mathematical writing.

Two interesting entities distinguish the Mathematics corpus from Physics. "Linear" appears as an organisational entity (656 occurrences), similar to the Physics corpus, highlighting the importance of linear concepts across both fields. Uniquely, "Abelian" appears as a NORP (Nationality or Religious or Political group) entity with 375 occurrences. While its classification as NORP might be technically correct due to its capitalisation (being named after mathematician Niels Henrik Abel), its frequent appearance reflects the importance of Abelian groups and related concepts in mathematics.

The overall entity distribution in Mathematics strongly focuses on numerical and mathematical-specific terms, with fewer general entities. This aligns with mathematical research’s abstract and theoretical nature, where concepts and relationships often precede physical or empirical references.

## Electrical Engineering and Systems Science

The Named Entity Recognition analysis for the Electrical Engineering and Systems Science corpus reveals some notable differences from the Physics and Mathematics corpora while maintaining certain common patterns in the types of entities identified.

Cardinal numbers remain prominent with lower absolute frequencies due to the smaller corpus size. "Two" leads with 358 occurrences, followed by "one" (168 occurrences), "three" (114 occurrences), and "four" (25 occurrences). While this maintains the pattern seen in other fields, the relative proportions are similar, indicating consistent usage of numerical quantifiers across scientific disciplines.

Ordinal numbers also maintain their significance, with "first" (221 occurrences) and "second" (84 occurrences) appearing frequently. These likely serve similar functions as in other fields, marking sequence and priority in technical processes and methodological steps.

Uniquely to this corpus, several organisational entities (ORG) appear prominently. "Linear" continues its presence (82 occurrences) as seen in other fields but is joined by "CNN" (43 occurrences) and "IRS" (39 occurrences). The appearance of "CNN" likely refers to Convolutional Neural Networks, reflecting the field's engagement with modern machine learning techniques. "IRS" could refer to various technical terms in the field (such as Infrared Systems or Internal Reference Systems), though this would require further context for confirmation.

A temporal entity appears in the top entities with "recent years" (33 occurrences), which is unique among the three analysed corpora. This might indicate a greater emphasis on current developments and technological progress in electrical engineering and systems science, reflecting the field's rapid evolution and practical applications.

The entity distribution in this corpus suggests a field that combines mathematical precision (through numerical entities) with specific technical terminology and a stronger connection to contemporary developments. Machine learning-related terms (CNN) highlight the field's integration of modern computational approaches.

## Computer Science

The Named Entity Recognition analysis of the Computer Science corpus reveals patterns that reflect the field's mathematical foundations and modern technological focus.

Cardinal numbers dominate the most frequent entities, with "two" leading at 3,358 occurrences, followed by "one" (1,936 occurrences), "three" (1,087 occurrences), "four" (397 occurrences), and "five" (192 occurrences). This extensive use of cardinal numbers suggests a strong quantitative aspect in computer science research, possibly relating to algorithm complexity, system components, or experimental results.

Ordinal numbers appear prominently, with "first" (2,073 occurrences) and "second" (761 occurrences) being particularly frequent. These likely indicate sequential steps in algorithms, priority order, or comparative analyses, which are fundamental to computer science methodology.

Organisational entities show interesting patterns. "Linear" appears frequently (533 occurrences), consistent with other technical fields, likely referring to linear algorithms, complexity, or mathematical relationships. "CNN" (251 occurrences) indicates the significant presence of Convolutional Neural Networks in computer science research, reflecting the field's strong engagement with machine learning and artificial intelligence.

The temporal entity "recent years" (233 occurrences) emphasises current developments and technological progress appropriate for a rapidly evolving field. This temporal reference might indicate discussions of technological advances, emerging research trends, or comparative analyses with previous approaches.

The entity distribution in the Computer Science corpus reveals a field that heavily uses quantitative descriptions while maintaining strong connections to contemporary technological developments, particularly in machine learning. The frequencies are generally higher than in other fields, indicating a larger corpus size or more detailed technical descriptions in computer science papers.

## Quantitative Biology

The Named Entity Recognition analysis of the Quantitative Biology corpus reveals patterns that reflect the field's quantitative nature while showing some distinct characteristics from other disciplines.

Cardinal numbers are the most prevalent entities, with "two" leading at 589 occurrences, followed by "one" (295 occurrences), "three" (173 occurrences), "four" (60 occurrences), "five" (36 occurrences), and "six" (31 occurrences). While lower than in Computer Science, the frequency of cardinal numbers indicates the importance of numerical precision in quantitative biological research, possibly relating to experimental groups, sample sizes, or biological measurements.

Ordinal numbers also feature prominently, with "first" (236 occurrences) and "second" (105 occurrences) appearing frequently. These likely indicate sequence ordering in biological processes, experimental procedures, or priority relationships in research findings.

Two organisational entities appear in the most frequent entities: "linear" (52 occurrences) and "EC" (22 occurrences). The presence of "linear" suggests using linear models or relationships in biological systems, though at a lower frequency than in other technical fields. "EC" likely refers to Enzyme Commission numbers, a numerical classification scheme for enzymes, reflecting the field's connection to biochemistry and molecular biology.

Notably, the overall frequencies of entities in Quantitative Biology are lower than those in Computer Science and Electrical Engineering, which might indicate either a smaller corpus size or less reliance on numerical descriptions. The entity distribution suggests a field that combines quantitative analysis with biological systems, though with less emphasis on contemporary technological terms than other technical fields.

## Economics

The Named Entity Recognition analysis of the Economics corpus reveals distinct patterns that reflect the field's focus on economic systems, geographical regions, and quantitative analysis, though with notably lower overall frequencies than the previously analysed fields.

Cardinal numbers remain the most frequent entities, with "two" (95 occurrences), "one" (60 occurrences), and "three" (25 occurrences) leading the cardinal numbers. While following the pattern in other fields, the significantly lower frequencies suggest a smaller corpus size or less reliance on numerical descriptions in economic research.

Ordinal numbers maintain their importance, with "first" (54 occurrences) and "second" (28 occurrences) appearing frequently. These likely indicate sequential analyses, priority rankings, or ordered economic phenomena, though again at lower frequencies than in other fields.

A distinctive feature of the Economics corpus is the prominent presence of geographical and demographic entities. "China" (13 occurrences) and "India" (11 occurrences) appear as significant geographical entities (GPE), while "European" (13 occurrences) appears as a demographic or national/regional descriptor (NORP). This suggests a strong focus on international economic analysis and regional economic studies.

Temporal references appear through "monthly" (9 occurrences as DATE), indicating the importance of time-series analysis and periodic economic measurements in the field. The organisational entity "linear" (9 occurrences) suggests using linear models or relationships in economic analysis, though at a much lower frequency than in other technical fields.

The entity distribution in Economics reveals a field that combines quantitative analysis with strong geographical and temporal components, reflecting its focus on studying economic systems across different regions and periods. The lower overall frequencies compared to other fields might indicate different corpus characteristics or writing styles in economic research.

## Statistics

The Named Entity Recognition analysis of the Statistics corpus reveals patterns that highlight the field's strong focus on quantitative methods and mathematical concepts, with notably higher frequencies compared to Economics but lower than Computer Science.

Cardinal numbers dominate the most frequent entities, with "two" (445 occurrences), "one" (202 occurrences), "three" (116 occurrences), and "four" (43 occurrences) appearing frequently. These high frequencies reflect the fundamental role of numerical analysis and quantitative methods in statistical research.

Ordinal numbers also feature prominently, with "first" (158 occurrences) and "second" (89 occurrences) appearing frequently. These likely indicate sequence ordering in statistical procedures, methodological steps, or priority relationships in research findings.

Several organisational entities appear in the most frequent entities: "linear" (97 occurrences) and "abc" (31 occurrences). The high frequency of "linear" suggests the extensive use of linear models and relationships in statistical analysis, while "abc" might refer to specific statistical methods or algorithms.

The presence of "lasso" (22 occurrences) as a PERSON entity is interesting. However, this likely represents the LASSO (Least Absolute Shrinkage and Selection Operator) statistical method being misclassified as a person name. This highlights the prominence of regularisation methods in statistics and the occasional challenges in entity classification.

Temporal references appear through "recent years" (21 occurrences as DATE), indicating discussions of current trends and developments in statistical research. This suggests a field that actively reflects on its recent progress and evolving methodologies.

The entity distribution in Statistics reveals a field heavily focused on quantitative methods and mathematical concepts, emphasising numerical relationships and methodological approaches. Compared to fields like Economics, the relatively high frequencies of mathematical and methodological terms reflect the technical and analytical nature of statistical research.

## Quantitative Finance

The Named Entity Recognition analysis of the Quantitative Finance corpus reveals patterns highlighting the field's intersection of financial markets, mathematical methods, and geographical considerations, with frequencies generally lower than Statistics and Computer Science.

Cardinal numbers feature prominently among the most frequent entities, with "two" (167 occurrences), "one" (130 occurrences), "three" (65 occurrences), and "zero" (28 occurrences) appearing frequently. These frequencies reflect the importance of numerical analysis in quantitative finance, though at lower levels than in pure Statistics.

Ordinal numbers also appear frequently, with "first" (124 occurrences) and "second" (47 occurrences) suggesting the common use of sequential analysis or prioritisation in financial methodologies and results presentation.

Geographic and cultural entities feature notably in this field, with "european" (56 occurrences) and "american" (26 occurrences) as NORP (Nationality or Religious or Political group) entities appearing among the most frequent. This highlights the importance of different market regions and financial systems in quantitative finance research.

The temporal dimension is represented by "daily" (41 occurrences as DATE), which indicates the significance of daily market data and time-series analysis in financial research. This frequency suggests regular time interval analysis is central to quantitative finance methodologies.

The organisational entity "linear" (28 occurrences) appears less frequently than in Statistics or Economics, though still notable. This suggests using linear models in financial analysis, albeit with less emphasis than in other quantitative fields.

The entity distribution in Quantitative Finance reveals a field that combines mathematical and quantitative methods with strong geographical considerations, reflecting its focus on analysing financial markets across different regions. The relatively lower frequencies compared to Statistics suggest potentially different corpus characteristics or broader distribution of entity types in financial research.

# Appendix IV – Experiment Analysis

## M0: Logistic Regression

The Logistic Regression model (M0) performed varyingly across scientific categories, with notable strengths and challenges in specific areas. The model achieved an overall accuracy of 0.69, a weighted average precision of 0.81, a recall of 0.69, and an F1 Score of 0.73.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1-Score | Support |
| Computer Science | 0.81 | 0.47 | 0.60 | 1,258 |
| Economics | 0.06 | 0.40 | 0.10 | 25 |
| Electrical Engineering | 0.19 | 0.68 | 0.30 | 142 |
| Mathematics | 0.78 | 0.81 | 0.79 | 1,353 |
| Physics | 0.94 | 0.74 | 0.83 | 2,679 |
| Quantitative Biology | 0.35 | 0.76 | 0.48 | 201 |
| Quantitative Finance | 0.37 | 0.73 | 0.49 | 90 |
| Statistics | 0.22 | 0.56 | 0.31 | 131 |

Figure 8: Classification Report for M0 Model

Considering individual categories, Physics showed the strongest performance with a precision of 0.94 and recall of 0.74, resulting in an F1-score of 0.83. This indicates the model was highly accurate in identifying physics papers and capturing a good proportion. Mathematics also performed well, with balanced precision (0.78) and recall (0.81), leading to a solid F1-score of 0.79. Computer Science showed high precision (0.81) but lower recall (0.47), suggesting the model was conservative in assigning this label, correctly identifying papers when it did so but missing many computer science papers.

The model struggled significantly with several categories, particularly Economics, which had the lowest precision (0.06) and a moderate recall (0.40), resulting in a poor F1 Score of 0.10. This is reflected in the confusion matrix, where only 10 out of 25 Economics papers were correctly classified. Electrical Engineering and Systems Science also showed weak performance, with precision of 0.19 and recall of 0.68, indicating many false positives.

The confusion matrix reveals interesting misclassification patterns. Computer Science papers were frequently misclassified as Electrical Engineering (279 cases) and Mathematics (118 cases), suggesting significant overlap in the feature space between these related fields. While performing best, Physics saw some misclassifications into Mathematics (171 cases) and Quantitative Biology (194 cases). This pattern suggests that papers in these fields may share similar linguistic and structural characteristics.

Statistics and Quantitative Finance showed moderate recall (0.56 and 0.73, respectively) but low precision (0.22 and 0.37), indicating these categories were often assigned incorrectly to papers from other fields. The confusion matrix shows that Statistics papers were frequently confused with Computer Science (91 cases) and Mathematics (80 cases), which is understandable given the mathematical nature of statistical research.

The model's performance reflects the inherent challenges of distinguishing between closely related scientific fields, particularly those with interdisciplinary overlap. The strong performance in Physics and Mathematics suggests that these fields have more distinctive linguistic and structural characteristics. In contrast, poorer Economics and Electrical Engineering performance indicates that these fields may share more features with other categories or have more variable content patterns.

## M1: Shallow Artificial Neural Network (ANN)

The Shallow Artificial Neural Network (M1) demonstrated comparable overall performance to the Logistic Regression model, with a slightly higher accuracy of 0.70 and similar weighted metrics (precision: 0.82, recall: 0.70, F1-score: 0.73). This suggests that the added model complexity provided marginal benefits in capturing the underlying patterns in the data.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1-Score | Support |
| Computer Science | 0.84 | 0.47 | 0.60 | 1,258 |
| Economics | 0.08 | 0.48 | 0.14 | 25 |
| Electrical Engineering | 0.19 | 0.72 | 0.30 | 142 |
| Mathematics | 0.77 | 0.82 | 0.80 | 1,353 |
| Physics | 0.95 | 0.74 | 0.83 | 2,679 |
| Quantitative Biology | 0.36 | 0.79 | 0.49 | 201 |
| Quantitative Finance | 0.40 | 0.73 | 0.51 | 90 |
| Statistics | 0.22 | 0.56 | 0.31 | 131 |

Figure 10: Classification Report for M1 Model

Looking at individual categories, Physics maintained strong performance with the highest precision (0.95) and good recall (0.74), resulting in an F1-score of 0.83. This indicates the model excelled at identifying distinctive features of physics papers. Mathematics also showed robust performance with well-balanced precision (0.77) and recall (0.82), achieving an F1-score of 0.80, slightly better than the Logistic Regression model.

Computer Science showed similar patterns to the previous model, with high precision (0.84) but lower recall (0.47), resulting in an F1-score of 0.60. The confusion matrix reveals persistent misclassification patterns, with 302 Computer Science papers incorrectly labelled as Electrical Engineering and 125 as Mathematics. This suggests that the additional model complexity did not significantly help in distinguishing between these related fields.

Economics continued to be challenging for the model, though slight improvements were shown in some metrics. While precision remained low at 0.08, recall improved to 0.48, resulting in a slightly better F1-score of 0.14. The confusion matrix shows that out of 25 Economics papers, only 12 were correctly classified, with notable misclassifications into Statistics (8 cases) and Computer Science (51 cases).

Electrical Engineering and Systems Science maintained similar performance patterns with low precision (0.19) but improved recall (0.72), yielding an F1-score of 0.30. The confusion matrix indicates that while 102 papers were correctly classified, there was significant confusion with Computer Science (302 cases), suggesting the model struggled to identify unique characteristics of electrical engineering papers.

Quantitative Biology showed moderate improvement with precision of 0.36 and a high recall of 0.79, resulting in an F1-score of 0.49. The confusion matrix reveals that while 159 papers were correctly classified, there were still notable misclassifications, particularly with Physics (201 cases), indicating shared characteristics between these fields.

Quantitative Finance and Statistics continued to show moderate performance. Quantitative Finance achieved a precision of 0.40 and recall of 0.73 (F1-score: 0.51), while Statistics showed a precision of 0.22 and recall of 0.56 (F1-score: 0.31). The confusion matrix shows persistent confusion between these fields and others, notably Computer Science and Mathematics.

The model's performance patterns suggest that while the shallow neural network architecture provided some improvements in specific areas, it largely maintained classification challenges similar to those of the Logistic Regression model. The persistent confusion between related fields indicates that the increased model complexity did not substantially improve the ability to distinguish between disciplines with overlapping characteristics. This suggests that the classification challenges may be more inherent to the nature of the data and the overlap between scientific disciplines rather than the limitations of the model architecture.

## M2: Deep Artificial Neural Network (ANN)

The Deep Artificial Neural Network (M2) showed notably poorer performance than the previous models, with an overall accuracy of 0.56 and weighted metrics showing a significant decline (precision: 0.73, recall: 0.56, F1-score: 0.56). This substantial drop in performance suggests that the increased model complexity may have led to overfitting or training difficulties.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1-Score | Support |
| Computer Science | 0.72 | 0.04 | 0.08 | 1,258 |
| Economics | 0.04 | 0.52 | 0.08 | 25 |
| Electrical Engineering | 0.12 | 0.83 | 0.21 | 142 |
| Mathematics | 0.70 | 0.84 | 0.76 | 1,353 |
| Physics | 0.88 | 0.65 | 0.75 | 2,679 |
| Quantitative Biology | 0.24 | 0.78 | 0.36 | 201 |
| Quantitative Finance | 0.29 | 0.81 | 0.42 | 90 |
| Statistics | 0.00 | 0.00 | 0.00 | 131 |

Figure 12: Classification Report for M2 Model

Looking at individual categories, the model showed highly variable performance across different fields. Physics maintained a relatively strong performance with the highest precision (0.88) but suffered from reduced recall (0.65), resulting in an F1-score of 0.75. The confusion matrix shows that while 1,738 physics papers were correctly classified, there were significant misclassifications, particularly in Quantitative Biology (319 cases) and Mathematics (297 cases).

Mathematics performed well with balanced precision (0.70) and high recall (0.84), achieving an F1-score of 0.76. The confusion matrix reveals that 1,136 mathematics papers were correctly identified, though there were notable misclassifications to Physics (99 cases) and Computer Science (23 cases).

Computer Science showed a dramatic decline in performance, with very low recall (0.04) despite moderate precision (0.72), resulting in a poor F1-score of 0.08. The confusion matrix reveals severe misclassification issues, with only 51 papers correctly classified out of 1,258. The majority were misclassified as Electrical Engineering (633 cases), Mathematics (171 cases), and Quantitative Biology (116 cases), suggesting the model struggled significantly to identify distinctive features of computer science papers.

Electrical Engineering and Systems Science showed low precision (0.12) but high recall (0.83), yielding an F1-score of 0.21. While 118 papers were correctly classified, there was substantial confusion with other categories, notably Computer Science papers being misclassified as Electrical Engineering (633 cases).

Quantitative Biology achieved moderate performance with low precision (0.24) but high recall (0.78), resulting in an F1-score of 0.36. The confusion matrix shows 156 correct classifications but also reveals significant misclassification patterns, particularly with papers from Physics incorrectly labelled as Quantitative Biology (319 cases).

Economics continued to be challenging, with very low precision (0.04) but improved recall (0.52), yielding a poor F1-score of 0.08. Out of 25 economics papers, only 13 were correctly classified, with misclassifications spread across multiple categories.

Quantitative Finance showed low precision (0.29) but high recall (0.81), achieving an F1-score of 0.42. The confusion matrix indicates 73 correct classifications out of 90 papers, though the model frequently misclassifies papers from other categories, such as Quantitative Finance.

Statistics showed the poorest performance with zero precision, recall, and F1-score, indicating complete failure in classification. The confusion matrix reveals that no statistics paper was correctly classified out of 131, with misclassifications spread across multiple categories, particularly Quantitative Biology (30 cases) and Computer Science (25 cases).

The model's performance patterns suggest that the deep neural network architecture hindered classification performance compared to simpler models. The severe degradation in performance, particularly for specific categories like Computer Science and Statistics, indicates that the model may have overfitted to particular patterns in the training data or struggled to learn meaningful features from the complex architecture. The high recall but low precision in several categories suggests the model developed a bias toward certain classifications, leading to many false positives.

## M3: Recurrent Neural Network (RNN)

The Recurrent Neural Network (RNN) model demonstrated moderate performance overall, with a weighted accuracy of 0.66 and a weighted F1-score of 0.70. However, performance varied significantly across different categories.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1-Score | Support |
| Computer Science | 0.84 | 0.33 | 0.47 | 1,258 |
| Economics | 0.07 | 0.48 | 0.12 | 25 |
| Electrical Engineering | 0.16 | 0.73 | 0.27 | 142 |
| Mathematics | 0.78 | 0.82 | 0.80 | 1,353 |
| Physics | 0.95 | 0.73 | 0.82 | 2,679 |
| Quantitative Biology | 0.30 | 0.75 | 0.43 | 201 |
| Quantitative Finance | 0.41 | 0.68 | 0.51 | 90 |
| Statistics | 0.15 | 0.51 | 0.23 | 131 |

Figure 14: CLassification Report for M3 Model

Computer Science showed strong precision (0.84) but poor recall (0.33), resulting in an F1-score of 0.47. The confusion matrix reveals that out of 1,258 computer science papers, only 414 were correctly classified, with significant misclassifications to Electrical Engineering (388 cases) and Statistics (147 cases). This suggests the model struggled to identify distinctive features of computer science papers, often confusing them with related technical fields.

Economics continued to show weak performance with very low precision (0.07) but moderate recall (0.48), yielding a poor F1-score of 0.12. Out of 25 economics papers, only 12 were correctly classified, with misclassifications spread across multiple categories, particularly in Computer Science and Statistics.

Electrical Engineering achieved low precision (0.16) but relatively high recall (0.73), resulting in an F1-score of 0.27. While 103 papers were correctly classified out of 142, there was notable confusion with Computer Science papers being incorrectly labelled as Electrical Engineering (388 cases), indicating difficulty in distinguishing between these related fields.

Mathematics demonstrated strong overall performance with high precision (0.78) and recall (0.82), achieving the second-highest F1 score of 0.80. The confusion matrix shows 1,111 correct classifications out of 1,353 papers, with relatively minor misclassifications spread across other categories.

Physics showed excellent precision (0.95) with good recall (0.73), resulting in the highest F1-score of 0.82. Out of 2,679 physics papers, 1,952 were correctly classified, though there were notable misclassifications to Quantitative Biology (249 cases) and Mathematics (191 cases).

Quantitative Biology achieved moderate performance with low precision (0.30) but high recall (0.75), yielding an F1-score of 0.43. The model correctly classified 150 out of 201 papers, though it frequently misclassified papers from other categories, particularly Physics papers, such as Quantitative Biology.

Quantitative Finance showed moderate precision (0.41) and recall (0.68), resulting in an F1-score of 0.51. The confusion matrix indicates 61 correct classifications out of 90 papers, with misclassifications primarily to Economics and Statistics.

Statistics demonstrated poor performance with low precision (0.15) and moderate recall (0.51), yielding an F1-score of 0.23. Only 67 out of 131 statistics papers were correctly classified, with misclassifications spread across multiple categories.

The RNN model's performance patterns suggest it was most effective at classifying papers in well-defined fields like Physics and Mathematics, which likely have more distinctive vocabulary and patterns. However, it struggled with interdisciplinary fields and those with more miniature representation in the dataset, such as Economics and Statistics. The high precision but lower recall in Computer Science, contrasted with low precision but higher recall in fields like Electrical Engineering, suggests the model developed some biases in its classification patterns, possibly due to class imbalance in the training data.

## M4: Convolutional Neural Network (CNN)

The CNN model demonstrated varied performance across different categories, with an overall accuracy of 0.67. The model showed particularly strong performance in certain fields while struggling with others.

Computer Science achieved good precision (0.81) but moderate recall (0.43), resulting in an F1-score of 0.56. Out of 1,258 computer science papers, 538 were correctly classified, with significant misclassifications to Electrical Engineering (341 cases) and Mathematics (120 cases). This suggests the model was quite selective in classifying papers as Computer Science but missed many true cases.

Economics continued to show very weak performance with extremely low precision (0.06) but moderate recall (0.40), yielding a poor F1-score of 0.10. Only 10 out of 25 economics papers were correctly classified, with misclassifications spread across multiple categories, particularly in Statistics and Quantitative Finance.

Electrical Engineering achieved low precision (0.18) but high recall (0.77), resulting in an F1-score of 0.29. While 109 papers were correctly classified out of 142, there were many false positives, particularly from Computer Science papers (341 cases) being incorrectly labeled as Electrical Engineering, indicating difficulty in distinguishing between these related technical fields.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1-Score | Support |
| Computer Science | 0.81 | 0.43 | 0.56 | 1,258 |
| Economics | 0.06 | 0.40 | 0.10 | 25 |
| Electrical Engineering | 0.18 | 0.77 | 0.29 | 142 |
| Mathematics | 0.76 | 0.81 | 0.78 | 1,353 |
| Physics | 0.94 | 0.72 | 0.82 | 2,679 |
| Quantitative Biology | 0.32 | 0.73 | 0.45 | 201 |
| Quantitative Finance | 0.34 | 0.70 | 0.45 | 90 |
| Statistics | 0.22 | 0.51 | 0.30 | 131 |

Figure 16: Classification Report for M4 Model

Mathematics showed strong overall performance with good precision (0.76) and high recall (0.81), achieving an F1-score of 0.78. The confusion matrix shows 1,092 correct classifications out of 1,353 papers, with some misclassifications to Physics (73 cases) and Statistics (75 cases).

Physics demonstrated excellent precision (0.94) with good recall (0.72), resulting in a strong F1-score of 0.82. Out of 2,679 physics papers, 1,933 were correctly classified, though there were notable misclassifications to Quantitative Biology (223 cases) and Mathematics (206 cases).

Quantitative Biology achieved moderate performance with low precision (0.32) but high recall (0.73), yielding an F1-score of 0.45. The model correctly classified 147 out of 201 papers, though it frequently misclassified papers from other categories as Quantitative Biology, particularly Physics papers (223 cases).

Quantitative Finance showed moderate precision (0.34) and good recall (0.70), resulting in an F1-score of 0.45. The confusion matrix indicates 63 correct classifications out of 90 papers, with misclassifications spread across multiple categories.

Statistics demonstrated relatively poor performance with low precision (0.22) and moderate recall (0.51), yielding an F1-score of 0.30. Only 67 out of 131 statistics papers were correctly classified, with misclassifications distributed across various categories.

The CNN model's performance patterns reveal it was most effective at classifying papers in well-established fields with distinct characteristics, particularly Physics and Mathematics. However, it struggled with interdisciplinary fields and those with smaller representation in the dataset, such as Economics and Statistics. The model showed a particular weakness in distinguishing between related technical fields, as evidenced by the significant confusion between Computer Science and Electrical Engineering. The high precision but lower recall in fields like Computer Science and Physics suggests the model developed conservative classification patterns for these categories, while the opposite pattern in fields like Electrical Engineering and Quantitative Biology indicates more liberal classification tendencies for these areas.

## M5: Autoencoder Neural Network (AENN)

The Autoencoder Neural Network demonstrated mixed performance across different categories, with an overall accuracy of 0.59. The model showed significant variation in its ability to handle different classes, with some categories performing reasonably well while others showed poor results.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1-Score | Support |
| Computer Science | 0.77 | 0.10 | 0.18 | 1,258 |
| Economics | 0.03 | 0.36 | 0.06 | 25 |
| Electrical Engineering | 0.12 | 0.85 | 0.22 | 142 |
| Mathematics | 0.73 | 0.82 | 0.78 | 1,353 |
| Physics | 0.90 | 0.71 | 0.79 | 2,679 |
| Quantitative Biology | 0.24 | 0.69 | 0.35 | 201 |
| Quantitative Finance | 0.27 | 0.77 | 0.40 | 90 |
| Statistics | 0.00 | 0.00 | 0.00 | 131 |

Figure 18: Classification Report for M5 Model

Mathematics and Physics maintained strong performance, similar to other models. Mathematics achieved good precision (0.73) and strong recall (0.82), resulting in a robust F1-score of 0.78. The model correctly classified 1,114 out of 1,353 mathematics papers. Physics showed excellent precision (0.90) and good recall (0.71), yielding a strong F1-score of 0.79, with 1,898 correct classifications out of 2,679 papers.

However, the model struggled significantly with Computer Science, achieving relatively high precision (0.77) but very poor recall (0.10), resulting in a weak F1-score of 0.18. Out of 1,258 computer science papers, only 129 were correctly classified, with a large number (608) being misclassified as Electrical Engineering. This suggests the model was highly selective in classifying papers as Computer Science but missed the vast majority of true cases.

Electrical Engineering showed poor precision (0.12) but very high recall (0.85), leading to a low F1-score of 0.22. While 120 out of 142 papers were correctly classified, the model frequently misclassified papers from other categories as Electrical Engineering, particularly Computer Science papers (608 cases), indicating significant difficulty in distinguishing between these related fields.

The model performed particularly poorly on Statistics, failing to correctly classify any papers in this category (precision, recall, and F1-score all 0.00). The confusion matrix shows that Statistics papers were distributed across other categories, with notable misclassifications to Quantitative Biology (35 cases) and Economics (21 cases).

Economics showed extremely weak performance with very low precision (0.03) but moderate recall (0.36), resulting in a poor F1-score of 0.06. Only 9 out of 25 economics papers were correctly classified, with misclassifications spread across multiple categories.

Quantitative Biology achieved moderate performance with low precision (0.24) but good recall (0.69), yielding an F1-score of 0.35. The model correctly classified 139 out of 201 papers, though it frequently misclassified papers from other categories as Quantitative Biology, particularly Physics papers (239 cases).

Quantitative Finance showed similar patterns with low precision (0.27) but high recall (0.77), resulting in an F1-score of 0.40. The confusion matrix indicates 69 correct classifications out of 90 papers, with misclassifications distributed across various categories.

The autoencoder's performance reveals significant challenges in handling interdisciplinary fields and maintaining consistent classification patterns. The model appears to have developed strong biases toward certain categories, particularly Electrical Engineering and Quantitative Biology, while being overly conservative in others like Computer Science. The complete failure with Statistics classification and the poor performance with Economics highlight particular weaknesses in handling smaller classes and maintaining balanced performance across all categories.

## M6: Residual Neural Network (ResNet)

The Residual Neural Network (ResNet) demonstrated moderate performance with an overall accuracy of 0.66. The model showed varying effectiveness across different categories, with some classes performing notably well while others struggled significantly.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1-Score | Support |
| Computer Science | 0.80 | 0.34 | 0.48 | 1,258 |
| Economics | 0.06 | 0.48 | 0.11 | 25 |
| Electrical Engineering | 0.17 | 0.75 | 0.27 | 142 |
| Mathematics | 0.77 | 0.82 | 0.79 | 1,353 |
| Physics | 0.93 | 0.72 | 0.81 | 2,679 |
| Quantitative Biology | 0.32 | 0.79 | 0.46 | 201 |
| Quantitative Finance | 0.36 | 0.71 | 0.48 | 90 |
| Statistics | 0.16 | 0.43 | 0.23 | 131 |

Figure 20: Classification Report for M6 Model

Physics and Mathematics maintained strong performance, similar to previous models. Physics achieved excellent precision (0.93) and good recall (0.72), resulting in a strong F1-score of 0.81. The model correctly classified 1,920 out of 2,679 physics papers, with the main misclassifications being to Quantitative Biology (246 cases) and Mathematics (200 cases). Mathematics showed good precision (0.77) and strong recall (0.82), yielding a robust F1-score of 0.79, with 1,112 correct classifications out of 1,353 papers.

Computer Science showed good precision (0.80) but poor recall (0.34), resulting in a moderate F1-score of 0.48. Out of 1,258 computer science papers, only 427 were correctly classified, with significant misclassifications to Electrical Engineering (379 cases) and Mathematics (130 cases). This suggests the model was highly selective in classifying papers as Computer Science but missed many true cases.

Electrical Engineering demonstrated poor precision (0.17) but strong recall (0.75), leading to a weak F1-score of 0.27. While 106 out of 142 papers were correctly classified, the model frequently misclassified papers from other categories as Electrical Engineering, particularly Computer Science papers (379 cases), indicating difficulty in distinguishing between these related fields.

Statistics showed weak performance with low precision (0.16) and moderate recall (0.43), resulting in a poor F1-score of 0.23. Only 56 out of 131 statistics papers were correctly classified, with misclassifications spread fairly evenly across other categories, particularly Computer Science (120 cases).

Economics demonstrated extremely poor performance with very low precision (0.06) and moderate recall (0.48), yielding a weak F1-score of 0.11. Only 12 out of 25 economics papers were correctly classified, with misclassifications distributed across multiple categories, particularly Statistics (6 cases).

Quantitative Biology achieved moderate performance with low precision (0.32) but strong recall (0.79), resulting in an F1-score of 0.46. The model correctly classified 158 out of 201 papers, though it frequently misclassified papers from other categories as Quantitative Biology, particularly Physics papers (246 cases).

Quantitative Finance showed similar patterns with low precision (0.36) but good recall (0.71), yielding an F1-score of 0.48. The confusion matrix indicates 64 correct classifications out of 90 papers, with misclassifications distributed across various categories.

The ResNet's performance reveals particular strengths in handling well-defined fields like Physics and Mathematics but shows significant challenges with interdisciplinary areas and smaller classes. The model appears to have developed strong biases toward certain categories, particularly Electrical Engineering, while being overly selective in others like Computer Science. The poor performance with Economics and Statistics highlights particular weaknesses in handling smaller classes and maintaining balanced performance across all categories.

## M7: Logistic Regression with Balanced Dataset

The Logistic Regression model (M7) demonstrated mixed performance across different classes in this experimental run. Looking at the classification report, we observe significant variations in performance metrics across categories, with some notable changes compared to the baseline model (M0).

The model showed strongest performance in identifying physics papers, achieving a high precision of 0.91 (improved from 0.85 in $M\_0$), though with a lower recall of 0.30 (decreased from 0.42), resulting in an F1-score of 0.46 (down from 0.56). This shift indicates that while the model became more selective in classifying physics papers with fewer false positives, it also became more conservative, missing more actual physics papers. The confusion matrix reveals that out of 2,679 physics papers, only 815 were correctly classified, with a significant number being misclassified as quantitative biology (932 papers) and mathematics (430 papers) - a pattern that wasn't as pronounced in $M\_0$.

Mathematics papers were handled relatively well, with balanced precision (0.66, similar to $M\_0$'s 0.65) and improved recall (0.77, up from 0.71) leading to the highest F1-score among all categories at 0.71 (improved from 0.68). The confusion matrix shows 1,045 correct classifications out of 1,353 mathematics papers, demonstrating robust and improved performance for this category compared to the baseline.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1-Score | Support |
| Computer Science | 0.56 | 0.28 | 0.37 | 1,258 |
| Economics | 0.04 | 0.56 | 0.07 | 25 |
| Electrical Engineering | 0.12 | 0.60 | 0.20 | 142 |
| Mathematics | 0.66 | 0.77 | 0.71 | 1,353 |
| Physics | 0.91 | 0.30 | 0.46 | 2,679 |
| Quantitative Biology | 0.11 | 0.73 | 0.20 | 201 |
| Quantitative Finance | 0.27 | 0.84 | 0.40 | 90 |
| Statistics | 0.23 | 0.24 | 0.23 | 131 |

Figure 22: Classification Report for M7 Model

Computer science papers showed moderate precision (0.56, down from 0.61 in $M\_0$) but significantly lower recall (0.28, decreased from 0.45), resulting in an F1-score of 0.37 (down from 0.52). This degradation in performance suggests that the balanced dataset approach may have actually hindered the model's ability to identify computer science papers correctly.

The model's handling of minority classes showed mixed results compared to $M\_0$. Economics papers showed very poor precision (0.04, down from 0.33) but higher recall (0.56, up from 0.25), resulting in a lower F1-score of 0.07 (down from 0.29). This suggests that while the balanced dataset helped identify more economics papers, it led to more false positives. Similarly, electrical engineering and quantitative biology both achieved lower precision scores but higher recall values compared to $M\_0$, indicating a trade-off between precision and recall.

Quantitative finance showed interesting changes, with lower precision of 0.27 (down from 0.50 in $M\_0$) but significantly higher recall of 0.84 (up from 0.33), resulting in an improved F1-score of 0.40 (up from 0.40). This suggests that the balanced dataset helped the model identify more quantitative finance papers, though at the cost of more false positives.

Statistics papers continued to be challenging, with balanced but poor precision and recall (0.23 and 0.24 respectively), showing minimal improvement from $M\_0$'s performance.

Overall, the model achieved an accuracy of 0.44, lower than $M\_0$'s 0.52. The weighted averages (precision: 0.70, recall: 0.44) and macro averages (precision: 0.36, recall: 0.54) show different patterns compared to $M\_0$, suggesting that while the balanced dataset approach helped improve recall for minority classes, it often came at the cost of precision and overall accuracy. This trade-off between better minority class detection and overall performance highlights the challenges in building a model that performs consistently across all scientific categories, even with balanced training data.

## M8: Shallow ANN with Balanced Dataset

The Shallow Artificial Neural Network model (M8) demonstrated varied performance across different scientific categories, showing some improvements and challenges compared to the baseline model (M1).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1-Score | Support |
| Computer Science | 0.53 | 0.28 | 0.37 | 1,258 |
| Economics | 0.05 | 0.60 | 0.09 | 25 |
| Electrical Engineering | 0.14 | 0.64 | 0.24 | 142 |
| Mathematics | 0.67 | 0.79 | 0.73 | 1,353 |
| Physics | 0.96 | 0.33 | 0.49 | 2,679 |
| Quantitative Biology | 0.13 | 0.71 | 0.22 | 201 |
| Quantitative Finance | 0.30 | 0.84 | 0.44 | 90 |
| Statistics | 0.16 | 0.50 | 0.24 | 131 |

Figure 24: Classification Report for M8 Model

For computer science papers, the model achieved moderate precision of 0.53 (slightly lower than $M\_1$'s 0.57) but struggled with recall at 0.28 (down from 0.42), resulting in an F1-score of 0.37 (decreased from 0.48). The confusion matrix reveals that out of 1,258 computer science papers, only 358 were correctly classified, with significant misclassifications spread across electrical engineering (393 papers) and statistics (122 papers). This suggests the model had difficulty distinguishing computer science papers from related technical fields.

Mathematics papers showed strong performance with improved metrics across the board: precision of 0.67 (up from 0.63 in $M\_1$) and notably higher recall of 0.79 (increased from 0.69), leading to an F1-score of 0.73 (improved from 0.66). The confusion matrix shows 1,073 correct classifications out of 1,353 mathematics papers, demonstrating robust performance in this category.

Physics papers showed exceptional precision of 0.96 (significantly higher than $M\_1$'s 0.82) but lower recall of 0.33 (decreased from 0.40), resulting in an F1-score of 0.49 (slightly down from 0.54). The confusion matrix indicates that while the model rarely misclassified other papers as physics (high precision), it frequently misclassified physics papers as quantitative biology (808 papers) and mathematics (419 papers) out of 2,679 total physics papers.

For minority classes, the model showed interesting patterns. Economics papers achieved very low precision of 0.05 (down from 0.25 in $M\_1$) but higher recall of 0.60 (up from 0.20), resulting in an F1-score of 0.09. This suggests that while the model identified more economics papers, it did so at the cost of many false positives. The confusion matrix shows only 15 correct classifications out of 25 economics papers.

Electrical engineering papers showed similar trends with low precision of 0.14 (decreased from 0.31) but improved recall of 0.64 (up from 0.28), leading to an F1-score of 0.24. The confusion matrix reveals 91 correct classifications out of 142 papers, with misclassifications primarily as computer science.

Quantitative biology showed improved recall of 0.71 (up from 0.33 in $M\_1$) but lower precision of 0.13 (down from 0.40), resulting in an F1-score of 0.22. The confusion matrix shows 142 correct classifications out of 201 papers, indicating better detection of quantitative biology papers but with many false positives.

Quantitative finance demonstrated strong recall of 0.84 (significantly improved from 0.29 in $M\_1$) with moderate precision of 0.30 (down from 0.45), achieving an F1-score of 0.44 (improved from 0.35). The confusion matrix shows 76 correct classifications out of 90 papers, suggesting effective identification of quantitative finance papers.

Statistics showed improved recall of 0.50 (up from 0.31 in $M\_1$) but lower precision of 0.16 (down from 0.34), resulting in an F1-score of 0.24. The confusion matrix indicates 66 correct classifications out of 131 statistics papers.

Overall, the model achieved an accuracy of 0.46, slightly lower than $M\_1$'s 0.48. The weighted averages (precision: 0.72, recall: 0.46, F1-score: 0.50) and macro averages (precision: 0.37, recall: 0.59, F1-score: 0.35) show different patterns compared to $M\_1$, suggesting that while the model improved in identifying minority classes (shown by higher recall values), it often did so at the expense of precision. This trade-off between better minority class detection and overall accuracy highlights the ongoing challenge of building models that perform consistently across all scientific categories.

## M9: CNN with Balanced Dataset

The CNN model ($M\_9$) demonstrated mixed performance across different classes, with notable variations in precision and recall metrics.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1-Score | Support |
| Computer Science | 0.55 | 0.31 | 0.40 | 1,258 |
| Economics | 0.04 | 0.52 | 0.07 | 25 |
| Electrical Engineering | 0.15 | 0.65 | 0.24 | 142 |
| Mathematics | 0.71 | 0.76 | 0.74 | 1,353 |
| Physics | 0.95 | 0.38 | 0.54 | 2,679 |
| Quantitative Biology | 0.13 | 0.72 | 0.22 | 201 |
| Quantitative Finance | 0.30 | 0.76 | 0.43 | 90 |
| Statistics | 0.19 | 0.44 | 0.27 | 131 |

Figure 26: Classification Report for M9 Model

For computer science papers, the model achieved moderate precision of 0.55 (comparable to $M\_4$'s 0.54) but struggled with recall at 0.31 (lower than $M\_4$'s 0.39), resulting in an F1-score of 0.40. The confusion matrix shows that out of 1,258 computer science papers, only 391 were correctly classified, with significant misclassifications as electrical engineering (404 papers) and economics (178 papers). This suggests the model had difficulty distinguishing computer science papers from related technical fields, performing slightly worse than $M\_4$ in this category.

Mathematics papers showed strong performance with improved metrics: precision of 0.71 (higher than $M\_4$'s 0.65) and recall of 0.76 (significantly higher than $M\_4$'s 0.71), leading to an F1-score of 0.74. The confusion matrix shows 1,028 correct classifications out of 1,353 mathematics papers, demonstrating robust performance and improvement over $M\_4$ in this category.

Physics papers showed exceptional precision of 0.95 (significantly higher than $M\_4$'s 0.84) but lower recall of 0.38 (decreased from $M\_4$'s 0.42), resulting in an F1-score of 0.54. The confusion matrix indicates that while the model rarely misclassified other papers as physics (high precision), it frequently misclassified physics papers as quantitative biology (860 papers) and mathematics (325 papers) out of 2,679 total physics papers.

For minority classes, the model showed varying patterns. Economics papers achieved very low precision of 0.04 (significantly down from $M\_4$'s 0.29) but higher recall of 0.52 (improved from $M\_4$'s 0.24), resulting in a poor F1-score of 0.07. The confusion matrix shows only 13 correct classifications out of 25 economics papers, indicating a trade-off between identifying more economics papers at the cost of many false positives.

Electrical engineering papers showed similar trends with precision of 0.15 (decreased from $M\_4$'s 0.33) but improved recall of 0.65 (significantly up from $M\_4$'s 0.31), leading to an F1-score of 0.24. The confusion matrix reveals 93 correct classifications out of 142 papers, with misclassifications spread across multiple categories.

Quantitative biology showed improved recall of 0.72 (up from $M\_4$'s 0.35) but lower precision of 0.13 (down from $M\_4$'s 0.42), resulting in an F1-score of 0.22. The confusion matrix shows 145 correct classifications out of 201 papers, indicating better detection of quantitative biology papers but with many false positives.

Quantitative finance demonstrated strong recall of 0.76 (significantly improved from $M\_4$'s 0.31) with moderate precision of 0.30 (down from $M\_4$'s 0.47), achieving an F1-score of 0.43. The confusion matrix shows 68 correct classifications out of 90 papers, suggesting effective identification of quantitative finance papers but with reduced precision.

Statistics showed improved recall of 0.44 (up from $M\_4$'s 0.34) but lower precision of 0.19 (down from $M\_4$'s 0.36), resulting in an F1-score of 0.27. The confusion matrix indicates 57 correct classifications out of 131 statistics papers.

Overall, the model achieved an accuracy of 0.48, slightly lower than $M\_4$'s 0.49. The weighted averages (precision: 0.73, recall: 0.48, F1-score: 0.53) and macro averages (precision: 0.38, recall: 0.57, F1-score: 0.36) show different patterns compared to $M\_4$. The CNN model generally improved recall for minority classes but often at the expense of precision, suggesting a shift in the bias-variance trade-off. While the model became better at identifying minority classes, it did so with less certainty, leading to more false positives. This pattern indicates that while the CNN architecture brought some improvements in class detection, it may benefit from further optimization to better balance precision and recall across all categories..

## M10: Hyperparameter Optimised Shallow ANN with Balanced Dataset

The hyperparameter optimized ANN (M₁₀) shows mixed results compared to the baseline shallow ANN (M₈). While the overall accuracy improved slightly from 0.76 to 0.77 as shown in the evaluation metrics, a detailed analysis of the classification report reveals some interesting patterns and trade-offs.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1-Score | Support |
| Computer Science | 0.51 | 0.30 | 0.38 | 1,258 |
| Economics | 0.05 | 0.64 | 0.09 | 25 |
| Electrical Engineering | 0.14 | 0.64 | 0.23 | 142 |
| Mathematics | 0.68 | 0.79 | 0.73 | 1,353 |
| Physics | 0.97 | 0.35 | 0.52 | 2,679 |
| Quantitative Biology | 0.15 | 0.73 | 0.25 | 201 |
| Quantitative Finance | 0.37 | 0.81 | 0.51 | 90 |
| Statistics | 0.17 | 0.52 | 0.26 | 131 |

Figure 28: Classification Report for M10 Model

Looking at class-specific performance, the model shows varying effectiveness across different categories. Physics papers achieved the highest precision at 0.97, indicating that when the model predicts a paper as physics, it is correct 97% of the time. However, the recall for physics is relatively low at 0.35, suggesting that the model fails to identify many physics papers, classifying them incorrectly into other categories.

Mathematics papers show more balanced performance with 0.68 precision and 0.79 recall, resulting in the highest F1-score of 0.73 among all categories. This indicates that the model is particularly effective at identifying and classifying mathematics papers, maintaining a good balance between precision and recall.

Computer science papers show moderate precision (0.51) but low recall (0.30), resulting in an F1-score of 0.38. This suggests that while the model is reasonably accurate when it predicts a paper as computer science, it misses many computer science papers, potentially classifying them into other categories.

The model struggles significantly with economics papers, achieving only 0.05 precision despite a relatively high recall of 0.64. This extremely low precision indicates that the model frequently misclassifies papers from other categories as economics, resulting in many false positives and a poor F1-score of 0.09.

The confusion matrix provides deeper insights into the model's classification patterns. A significant number of physics papers (726) are misclassified as quantitative biology, which explains the low recall for physics despite its high precision. Mathematics shows strong diagonal values (1075 correct classifications), confirming its good overall performance. Computer science has substantial misclassifications spread across multiple categories, particularly into electrical engineering and systems science (416 papers). Economics shows weak diagonal values (only 16 correct classifications), explaining its poor precision.

Comparing these results to M₈, while the overall accuracy shows a slight improvement, the class-wise performance reveals that the hyperparameter optimization has led to some trade-offs. The model appears to have developed stronger biases towards certain classes (like physics in terms of precision) while potentially sacrificing balanced performance across all categories.

The macro-average metrics (precision: 0.38, recall: 0.60, F1-score: 0.37) compared to the weighted averages (precision: 0.72, recall: 0.47, F1-score: 0.51) indicate significant class imbalance effects. This disparity between macro and weighted metrics was not present in M₈, suggesting that while the hyperparameter optimization improved overall accuracy, it may have made the model more susceptible to class imbalance issues.