A Mini Project Report

On

Neural Network Design with Natural Language Processing

Submitted in the Partial Fulfillment of the Requirements

For the Award of the Degree of

Bachelor of Technology

In

CSE (Artificial Intelligence and Machine Learning)

By

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CERTIFICATE

This is to Certify that the Mini Project Entitled "**Neural Network Design with Natural Language Processing**" Being Submitted By

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In Partial Fulfillment of the Requirements for the Award of Degree of Bachelor of Technology in CSE (Artificial Intelligence and Machine Learning) to B V Raju Institute of Technology is Record of Bonafide Work Carried Out During the Period from December 2024 to May 2025 by Them Under the Supervision of

Ms. Srilakshmi V	**Assistant Professor**
Dr. G Uday Kiran	**Associate Professor**

This is to Certify that the Above Statement Made by the Students are Correct to the Best of Our Knowledge.

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CANDIDATE'S DECLARATION

I Hereby Certify that the Work Which is Being Presented in the Mini Project Entitled "Neural Network Design with Natural Language Processing" in Partial Fulfillment of the Requirements For the Award of Degree of Bachelor of Technology and Submitted in the Department of CSE(Artificial Intelligence and Machine Learning), B V Raju Institute of Technology, Narsapur, is an Authentic Record of My Own Work Carried Out During the Period From December 2024 to May 2025, Under the Supervision of Dr. G Uday Kiran, Program Coordinator and Ms. Srilakshmi V, Assistant Professor.

The Work Presented in this Mini Project Report Has Not Been Submitted By Me For the Award of Any Other Degree of This or Any Other Institute/University.

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I stand at the culmination of a significant journey, one that has been both challenging and rewarding. The success of my mini project is not solely a reflection of my efforts but a testament to the invaluable support and guidance I have received from many quarters. It is with deep gratitude that I acknowledge those who have made this achievement possible.

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ABSTRACT

Creating deep learning models generally requires a considerable technical skill that can be hard for unintended users to access, which can also limit productivity for technical practitioners. This project document outlines a user centered, completely automated deep learning system that is designed to resolve some of these issues and allow users to go from natural language to design and deploy optimized neural network architectures automatically, without writing code or designing an architecture.

The system relies on the integration of Natural Language Processing (NLP) and the AutoKeras framework. The NLP module parses the user free-form input to elicit the essential parameters of: the task category, the task type, and any optional hyperparameters or dataset references. The parameters are then passed to AutoKeras, which uses Neural Architecture Search (NAS) to automatically construct, train, and optimize the best model architecture for the user defined task. From model development to model deployment, this system is completely automatic.

For the sake of expanding usability for different user groups, the automated system can also provide multilingual input and output support. Users can interact with the system in any language of their choice, and the system will give the user translated outputs Model descriptions and performance summaries will be provided in the user's preferred language. The multilingual capabilities of the automated system make the process of deep learning development that includes all users, and is possible for more globally relevant initiatives.

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LIST OF ABBREVIATIONS

S. No	Abbreviation	Full Form
1	AI	Artificial Intelligence
2	AutoML	Automated Machine Learning
3	NAS	Neural Architecture Search
4	NLU	Natural Language Understanding
5	NLP	Natural Language Processing
6	ML	Machine Learning
7	AutoKeras	Automated Keras (AutoML framework built on Keras)
8	BERT	Bidirectional Encoder Representations from Transformers
9	ChamNet	Channel-adaptive Neural Network
10	CNN	Convolutional Neural Network
11	DARTS	Differentiable Architecture Search
12	ENAS	Efficient Neural Architecture Search
13	FBNet	Facebook Net (Hardware-aware NAS framework)
14	FENAS	Feature-Engineering Neural Architecture Search
15	FLOPs	Floating Point Operations
16	FOX-NAS	Fast On-device eXploration Neural Architecture Search
17	GPT	Generative Pre-trained Transformer
18	GLUE	General Language Understanding Evaluation

19	GNN	Graph Neural Network
20	GPU	Graphics Processing Unit
21	MnasNet	Mobile Neural Architecture Search Network
22	NAS-Bench-NLP	Neural Architecture Search Benchmark for NLP
23	NASNet	Neural Architecture Search Network
24	Penn Treebank (PTB)	Text corpus for language modeling tasks
25	ProxylessNAS	Proxyless Neural Architecture Search
26	RNN	Recurrent Neural Network
27	SMOTE	Synthetic Minority Over-sampling Technique
28	SNAS	Stochastic Neural Architecture Search
29	CIFAR-10	Canadian Institute for Advanced Research 10 (image dataset)
30	LSTM	Long Short-Term Memory
31	GRU	Gated Recurrent Unit
32	ReLU	Rectified Linear Unit
33	RGB	Red Green Blue

CHAPTER 1
INTRODUCTION

1.1 Neural Architecture Generation

Building effective deep learning models, in practice, is often determined by how we configure the underlying neural network architectures. Until recently, the process was quite onerous, often requiring expert knowledge, numerous layer options, hyperparameter tuning, and trial and error. Encumbered by this complexity, it is often difficult for non-machine learning experts and beginners alike to get started. With the goal of providing more analysis capabilities to users who were less machine learning literate, the new fields of Automated Machine Learning (AutoML) and Neural Architecture Search (NAS) are providing exciting automated possibilities. An example is AutoKeras, which uses NAS to allow users to automatically fit a deep learning model again and again while avoiding complex model architecture specification.

To advance the work and make it even more accessible, the emerging fields of Automated Machine Learning (AutoML) and Neural Architecture Search (NAS) are providing possibilities for automation in research and development with tools such as AutoKeras. AutoKeras allows users to automatically create optimized deep learning models by leveraging NAS without worrying as much about the technical aspects of deep learning.

In this project, we will use AutoKeras to automate the development of neural network architecture. Essentially, we hope to reduce the amount of manual work put into the development of these initial architectures. Our hope is to extend the access to deep learning to users who come from different levels of technical aptitude while reducing the development and research cycle by automating certain repetitive aspects of predictive analytics. In effect, we create access to advanced deep learning models for a wide community. We extend the speed and velocity of innovation in deep learning applications.

1.2 Introduction to the Domain

Natural Language Processing (NLP) and Speech Processing are two areas of artificial intelligence that enable machines to understand and converse in human language. They can often be found in applications such as language translation programs and voice recognition software. Though many people rely on these technologies, this project takes a more user-entered approach by focusing on easing communication for users.

How NLP Works:

- Understanding the User Input: The engine analyzes your user input in detail to find important pieces of information included, such as what potential task you wish to do, the type of neural network you wish to use, and what types of activation functions you might be interested in using.
- Translating to Machine Language: Once the engine identifies all of those types of information, it effectively translates them into an ongoing structured process that the AutoKeras framework can understand.
- Feedback to the User: Finally, it provides you with a descriptive and logical output representation of the model it produced as a response to your command. We even created a feature to translate these descriptions into various languages, broadening access for users across the globe.

This functionality does not just simply standardize how users can interface with the system, but it provides greater flexibility and accessibility for individuals with various languages and levels of technical understanding of the technologies that are available. By using everyday language, we allow all users to use a similar intuitive language for operation when using a technology that is relatively advanced and highly sophisticated.

1.3 Relevant Techniques

This project takes a look at how we can automatically generate deep learning models by combining several cutting-edge techniques. The goal is to create a model-building experience that is not only efficient but also smart and tailored to the user.

- **AutoKeras:** AutoKeras is the main framework for automating the process of developing machine learning models. It is an open-source platform that is built on TensorFlow and Keras. Its primary advantage is its use of a method called Neural Architecture Search (NAS) - an automated method to discover and build high-quality deep learning models specifically tailored for the user's intentions.

- **Neural Architecture Search (NAS):** Neural architecture search (NAS) is a new way to automate the process of designing neural networks. Customarily, designing these networks is an extremely tough task, requiring countless hours and expert assistance. NAS helps alleviate the problem, by systematically attempting many different ways of building a network, before selecting the best architecture for a specific problem. This eliminates the necessity for bulk testing and expert decisions about the construction of the network.

- **Natural Language Understanding (NLU):** The naturally intuitive interface of our system includes a custom built Natural Language Understanding (NLU) components. This component of the system is engineered to ensure that it can intelligently pull-out salient detail from the text typed by users in a manner of natural communication. This allows users to describe what they want their model to do in their own words, and the system can intelligently translate this into the appropriate technical specifications.

- **Multilingual Translation:** In making the system useful and open to people from anywhere in the world, and given its strong multilingual translation capabilities, the system ensures that the description of the models created can be shown in any language desired by the user. Multilingual translation on the one hand makes the potential user base larger, increasing the ability for people from anywhere to be able to use the system while also helping more users access and are able to understand the system output, no matter what language they are speaking.

Together, all these methods lead to the automated generation of optimal neural network architectures directly from intuitive, natural language descriptions. The coordinated, integrated, coordinated yield is a significant step towards making advanced deep-learning methods more widely accessible.

1.4 Problem Statement

Creating a working neural network can be tricky. It often involves a mix of experience and expertise, as well as much trial and error. To make it work, you really should understand the principles of machine learning, be familiar with the different deep learning environments, and need to experiment and get your hands dirty with a collection of models.

These prerequisites create a considerable burden on many potential users, including students new to AI, those that come from non-technical fields, and interested parties wanting to evaluate an idea in a matter of days — without ever worrying about the more technical elements. As a result, many people are sidelined from ever taking the plunge into deep learning, or are limited to using models that are not acutely relevant to their interests.

We need to develop systems that will assist in the design of deep learning architectures, in a way that is easier, stimulates an efficient design process, and that everybody can utilize. Only then can more people engage with this interesting country and explore the unknown.

1.5 Objective

The primary objective of this initiative is to develop an intelligent, user-friendly platform that would allow anyone to build advanced deep-learning models by simply describing them in plain words. Designing neural networks can be complicated and intimidating, and we plan to take a promise to reduce that complexity.

To achieve our goal, we will set some concrete and measurable goals for us to make progress:

- We will let users describe their unique modelling needs in plain language, no technical jargon! We will extract the relevant aspects of the descriptions and transform them to structured format to allow computers to interpret them to in turn generate models automatically.
- Our platform will run AutoKeras and Neural Architecture Search (NAS) algorithms to automatically design and optimize neural networks for users, with no technical details or nitty-gritty required. Users should be able to focus on their project outcomes and applications.
- Each user will be able to benefit from built-in multilingual translation features, so they can receive model descriptions in their language of choice. The wider the audience can access and

understand the technology, the better as we all connect on a global scale.

- We will support a wide variety of deep learning tasks, including Image Classification, Text Classification, Time Series Forecasting, Regression, and Sentiment Analysis, to allow users to focus on their requirements.

Our holistic approach is focused on developing neural architectures in a more intuitive fashion and shortening development cycles. In turn, we aspire to increase inclusivity in the deep learning community to inspire creativity and help more individuals adopt state-of-the-art deep-learning technologies in a variety of applications.

CHAPTER 2
REVIEW OF LITERATURE

2.1 INTRODUCTION

The design of efficient neural network architectures is a pillar of successful deep learning applications. Creating those architectures can be difficult and require considerable amounts of expertise, thus requiring users to spend time experimenting and tuning hyperparameters, which can lead to missed opportunities to deploy models and, ultimately, reduce accessibility.

These related challenges have spawned new developments for how researchers and developers define and deploy neural network architectures. First, the emergence of Neural Architecture Search (NAS) as a means for the automation in discovering and optimizing neural network designs for deployment not only provides automation for efficiency purposes, but improves the generality of models across computational problems. Secondly, recent advances in the NLP domain allow casual users to naturally express environmental considerations, allowing them to use casual language to express nuanced, complex needs of what to perform.

By merging NLP with automated machine learning (AutoML) platforms such as AutoKeras, users simply describe their needs and the system generates smart models without needing elaborate manual configurations. Great multilingual support, on top of the complexity of the AI tools listed previously, will allow users to get value from these systems no matter what language they speak.

This will be the most expansive review of foundational and cutting-edge research on these topics and we will also proactively search for significant developments in Neural Architecture Search, NLP based model generation, and multilingual AI systems to provide the background knowledge for the new approach we will be taking in this project.

2.2 RELATED WORK

Zoph & Le [1] presented a NAS method using reinforcement learning to automate the design of CNNs and RNNs deep networks, reaching state-of-the-art performance on CIFAR-10 and PTB datasets. Though this process was expensive, it proved NAS as a viable alternative to manual design.

Pham et al. [2] introduced Efficient NAS (ENAS) that shared parameters among child models as it searched, which reduced the total computation by 1000 times compared to previous models while also achieving comparable accuracy. ENAS was also able to show the efficiency of NAS due to the weight sharing and the controller RNNs.

Liu et al. [3] included Differentiable Architecture Search (DARTS) that utilized continuous relaxation substitution for NAS, which replaces discrete search by gradient-based optimization. DARTS showed results comparable with reinforcement learning and evolutionary methods with much less computation. DARTS advanced the space by simplifying NAS without reinforcement learning.

Real et al. [4] showed that regularized evolution is better than reinforcement learning in architecture search, in their evolutionary approach they discovered high-performing networks on ImageNet without a lot of human bias. What was interesting about this work was that regularized evolution is simply a simpler evolutionary method without complex NAS tasks.

Elsken et al. [5] provided a comprehensive survey of NAS methods, benchmarks, and open challenges. Their review serves as an evaluation of trade-offs versus different search strategies, including; reinforcement learning, evolution, and gradient-based search methods. They stressed reproducibility and computational budget should be addressed first.

Luo et al. [6] framed the architecture search as a continuous optimization problem, applying gradient descent and eliminating reinforcement learning altogether. They also escaped reinforcement learning by producing an algorithm that applied incremental performance gains on image tasks while decreasing the handling of the NAS domain by decomposing the search space into inference models as required by reinforcement learning.

Li and Talwalkar [7] fed into the notion that random search approaches can perform equally well as state-of-the-art NAS methods. Their paper questioned reproducibility in strategies in the NAS literature and provided evidence that simple baselines perform equally well to complex algorithms on the standard benchmarks.

Jin et al. [8] created Auto-Keras, a relatively easy to use NAS framework that also includes Bayesian optimization. They automated NAS for non-expert practitioners and demonstrated promising results on image and text-based tasks with minimal user input as all aspects of the architecture, method and task were confined to predetermined search spaces.

Zhang et al. [9] examined the evolution of attention-augmented CNNs in an agentic mode, and they were able to find architectures that had improved accuracy-efficiency-trade-offs designs that are hand-crafted. The attention mechanisms were automatically mapped to a wide range of vision tasks and improved performance was achieved via search.

Zhou et al. [10] proposed an evolutionary NAS framework for multi-task optimization that made no task-specific assumptions about the nature of tasks resulting in a diverse portfolio of architectures which were exploitable to different computational constraints giving a more scalable flexibility in deploying deep neural networks in practice.

Chen et al. [11] filled in depth gaps in NAS with progressive DARTS, shutdowns gap between evaluating networks with a small number of shallow search with much fuller evaluation networks. Its ability to improve stability in searching deeper architectures was also an advantage in terms of the overall reliability of NAS.

Chu et al. [12] developed a NAS for multi-hardware deployment for mobile resources that was able to simultaneously optimize accuracy, latency and energy metrics, across all devices. The models that they generated were able to perform efficient inference and all the different hardware at the edge which showed the capabilities of NAS in realistic settings.

Jiang et al. [13] developed Russian Doll NAS, which builds architectures from inner subnetworks, where every subnetwork can be nested within the previous one. This enables studying architectures from simpler to complex, while also allowing a cheaper way to search a full-network.

Shen et al. [14] proposed plug-and-play blocks for modular NAS, where architectures can now be changed post-search and dynamically adjusted. This represents more flexibility about how changes can be made to NAS generated architecture models with some new constraints in mind, or combining NAS-generated architecture models.

Liu et al. [15] used FOX-NAS through zero-cost proxies that allowed on-device architecture search, to speed up hardware-aware optimization.

They discovered architectures tailored to specifics of mobile architecture processors suitable for later and efficient deployment.

Sun et al. [16] used genetic algorithms to evolve CNNs which reached state-of-the-art levels in image classification tasks with the potential to surpass those made manually. They demonstrated that evolutionary algorithms could be useful for finding architecture, while also continuing to automate model construction.

Xie et al. [17] introduced SNAS as a differentiable NAS approach that uses stochastic relaxation to balance the competing needs of fair gradient estimation during supernet training. SNAS partially eliminated biases present in previous differentiable methods Improving the validity of the architecture search results.

Chatzianastasis et al. [18] presented a NAS method based on Graph Neural Networks (GNN) for structured search spaces, highlighting the topological relationships of layers. This representation allows for much more flexibility and information to explore architectures.

Hospedales et al. [19] conducted a survey on the connection of meta-learning and NAS, emphasizing few-shot architecture adaption approaches. The authors highlighted potential overlaps of the two research areas, and possible future directions.

Piergiovanni et al. [20] proposed space-time NAS for video recognition, considering the length of 3D convolutions and temporal connectivity. Their proposed system is designed to automatically search for efficient architectures while improving performance for video based tasks.

Wang et al [21] proposed a framework called Text NAS for text-based Natural Language Processing, minimizing the need for manual design by automating the design of attention mechanisms as well as RNN cells.

It also provided neural architectures that were better than hand-designed models on GLUE benchmarks, showing that the use of NAS for text classification produces better models than humans.

Pasunuru and Bansal [22] presented a flexible framework for searching NLP architectures called FENAS which included dynamic feature engineering too. The FENAS approach surpassed previous state-of-the-art results on several language understanding tasks and exemplified improved flexibility in NLP.

Klyuchnikov et al. [23] introduced NAS-bench-NLP, a benchmarking dataset that included over 14,000 architectures for various language tasks with unified evaluation. The goal is to improve reproducibility of results and allow for better comparisons of NLP-focused approaches to NAS.

MacLaughlin et al. [24] examined the issues of NAS when applied to sentence-pair classification tasks and proposed cross-task generalization as one challenge. Their insights are helpful to improve robustness and adaptation in NLP tasks.

Cai et al [25] proposed ProxylessNAS, a framework that transcends proxy tasks in neural architecture search by searching directly on target datasets and hardware. This process removes proxy bias, creates a simpler NAS workflow, and gives more direct measures.

Wu et al. [26] developed FBNet, a hardware-aware NAS algorithm for mobile devices that exploits differentiable architecture search with the actual latency used as objective (instead of FLOPs). This allows for actual deployment on smartphones.

Tan et al. [27] introduced MnasNet, which proposed a multi-objective reward in order to balance latency and accuracy for mobile deployment.

This provides a platform-aware approach to utilize by products such as Google's EdgeTPUs to illustrate practical scalability.

Dai et al [28] put forth ChamNet, a framework that adapts networks architecture based on hardware limit with accuracy predictor for speed-up/evaluation. The architecture is a versatile framework that efficiently makes deployment that was based on specific model architecture for devices.

Xie et al. [29] challenged the assumed unrepeatability in hand-crafted networks by illustrating that randomly wired networks can result in similar performance vs. those wider hand-crafted networks. This raised questionable assumptions in network design.

Chen et al. [30] presented a progressive model growth strategy through network transformation, which transformed existing pretrained models into complex architectures. This had less computational cost while maintaining a high-performing model.

Zhong et al. [31], presented a block-wise search NAS strategy which builds models from reusable parts of architecture components. This enables modular construction of architecture to simplify search while keeping enough flexibility.

Zheng et al. [32] offered multinomial NAS that increased search for probabilistic search space by addressing the exploration-exploitation dilemma which enabled discovering diverse set of architectures that were good-performing.

Dong and Yang [33] proposed NAS using weight sharing and early stopping, allowing NAS to be conducted in 4 GPU hours, making NAS much easier to access for researchers with limited computational power.

Zhou et al. [34] offered Bayesian NAS, and introduced more uncertainty estimating for improving stability of evaluations. Probabilistic evaluations also help reduce variance maintaining reliability in the architecture performance assessment.

Le et al. [35] creatively applied NAS to time series forecasts focusing on hybridized from LSTM and temporal convolution architectures. The models discovered by search outperformed models created manually, enhancing predictive accuracy.

Tran and Nguyen [36] investigated NAS for dialogue systems by emphasizing relevant and rapid development in RNN-based sequence generation. They emphasize the potential of NAS to further improve conversational AI systems.

White et al. [37] proposed BANANAS, a NAS method using Bayesian optimization with neural acquisition functions. The method attained state-of-the-art performance on several benchmarks with fewer evaluations showing how efficient black-box optimization of architecture can be.

X. Hu et al. [38] Present a NAS system for end-to-end speech recognition, jointly optimizing the acoustic and language models which produces state-of-the-art performance on LibriSpeech dataset showing how effective NAS can be in the applications of speech. The NAS in speech recognition tasks further introduce the opportunity to improve model performance in audio processing application area.

C. Ying et al. [39] The authors introduce NAS-Bench101 consisting of 423,000 architecture evaluations for reproducible NAS research. This benchmark allows researchers to benchmark NAS methods with a common dataset and addition demonstrate a level of persistence and transparency. The benchmark will allow researchers to have a baseline tool for evaluating NAS approaches.

M. Kryuchkova et al. [40] This paper generalizes NAS benchmarking to natural language processing tasks through the addition of NAS-Bench-NLP, which contains 14,000 language architectures. The benchmark introduces a standardized medium for assessing NAS methods for NLP tasks, enabling estimates to be made regarding the performance of NAS methods, and allowing for comparisons between NAS methods as well as improvements in the state-of-the-art for methods developed later on. One of the goals of the authors was to fill in a gap in library of NAS benchmarking resources that are domain-specific.

H. Dong et al. [41] The authors describe NAS-Bench-201, a fixed search space benchmark that focuses on cell-based search spaces. The purpose of the benchmark is to standardize NAS evaluations on different datasets. A fixed search space and the overall performance level are provided as evaluation metrics, which will allow reproducible NAS research advancements to take place in the future. The benchmark can be useful for creating transferable architectures.

T. Chen et al. [42] Auto-Deep Lab is proposed as a hierarchical NAS method for semantic segmentation that optimizes both network architectures and cells serving as subcomponents. The authors report state-of-the-art semantic segmentation results on Cityscapes and PASCAL VOC datasets, highlighting the potential of hierarchical search strategies to improve network architecture performance, and how multi-scale feature learning should be an intentional effort when developing segmentation approaches.

A. Chatzianastasis et al. [43] The authors present a GNN-based NAS approach to use sampled embeddings, derived from learnt compatibility rules in layers. Because all neural architectures can be represented as graphs, the learned embeddings can allow for a flexible search space throughout different families to discover efficient designs. This study proved the potential for graph-based approaches to discover meaningful architectures.

L. Hou et al. [44] Single-DARTS is presented to improve the stability of differentiable NAS by replacing bi-level optimization with single-level optimization. This addresses performance collapse issues and enhances consistency in architecture search. The method achieves state-of-the-art performance for mainstream search spaces. CVF Open Access

S. Hochreiter and J. Schmidhuber [45] This landmark paper develops Long Short-Term Memory (LSTM) networks. By using "memory cells" to handle the vanishing gradient problem from the RNNs, a better approach for modeling long-term dependencies was created for sequential data. This work has had a tremendous influence on a variety of time-series problems. It also happens to be the work that laid the foundation for a range of recurrent NAS developments.

A. Vaswani et al. [46] made the complete elimination of recurrence and relied solely on self-attention for sequential information when they introduced the transformer. The benefits to the NLP community cannot be overstated, in some cases, providing improved predictions, and statistically significantly identical reliability to previous outcomes in a variety of applications (for example, review of state-of-the-art results for machine translation). This phenomenal performance, studies on adoption rates, and subsequent performance improvements by its competitors "borrowing" the architecture, makes the case for the transformer to often provide the basis of attention-based NAS.

K. He et al. [47] The residual connections contained in ResNet were introduced for the purpose of training very deep neural networks and combating the vanishing gradient problem. The skip connections allow for even deeper models to be built, increasing performance in image classification tasks over shallower models. The design principles of ResNet are foundational in modern NAS search spaces.

J. Liu et al. [48] Net Adapt is introduced as a platform-aware NAS method in which a network is pruned iteratively to accommodate hardware constraints. This method adapts pre-trained models with a focus on their deployment on mobile devices to find a balance between accuracy versus resource use. Net Adapt demonstrates the concept of hardware-aware NAS from an optimization perspective.

H. Cai et al. [49] Once-for-All (OFA) formulated a NAS framework in which only a single pathway was trained to support different ways the pathway could be formed. This provides for a decoupled training and search approach so that the model can be quickly specialized to consume hardware without the need to retrain the model. OFA competes very favorably against numerous other scenarios for deployment.

X. Guo et al. [50] The authors describe a Single-Path NAS, which frames the construction of architectures with a single path while keeping weight co-adaptation minimal, thus simplifying the training of a supernet. This method increases efficiency and efficacy of the training process especially for large-scale data sets such as ImageNet. This work adds realism to one-shot NAS methods.

T. Elsken et al. [51] proposed a new multi-objective NAS framework. A Lamarckian evolution method was utilized to optimize accuracy, latency, and energy consumption. The evolutionary algorithm enabled finding architectures that optimized for multiple criteria when deployed.

This work highlights the importance of multiple objectives when considering NAS.

M. Luo et al., [52] presented a method for learning architecture generators and applying them for segmentation tasks that allows for designs to be transferred across diverse datasets. This approach leverages transferable architectural knowledge in order to reduce computational expense of peoples' NAS in practice for each task. This study also serves to indicate the usefulness of meta-learning for people practicing NAS.

J. Song et al., [53] introduced an extension of ProxylessNAS that enabled different kinds of hardware to be used for the deployment of the architecture. This study enabled a let the system learn hardware specific adaptations automatically. This work indicates the necessity of hardware-aware NAS methods.

C. Xie and A. Yuille [54] may be the first paper to use genetic algorithms to design CNN architectures. This study illustrated the use of an evolutionary approach to NAS. This study is pivotal in NAS, for showing that architectures can be discovered automatically. This was an important step in the automation of neural network design.

H. Chen et al. [55] The authors enhance progressive NAS with an early stop mechanism that stops overfitting in a long search process, leading to better architectures and removes the anchor in doing it for a long time. It improves the NAS process.

Y. Lin et al. [56] A loss balancing method is used as an adaptive strategy that help stabilize DARTS to circumvent gradient dominance during optimization. This modification yields more reproducible and reliable search results. The article advances the robustness of differentiable NAS methods.

S. Park et al. [57] The study provided a method for NAS that used the objective criteria of inference speed, and accuracy for the targeted problem of time segmentation - the newly discovered models are deployable on edge devices, enhance inference performance, and effectively use system resources. This research demonstrates usable NAS methods within time constrained applications.

B. Zoph et al. [58] This research showed that architectures trained via a NAS method on datasets pertain to the CIFAR could generalize to larger datasets such as ImageNet. This confirms that NAS designed models exhibit generalization capability spanning level of context. This is evidence of the scalable implementation of NAS.

H. Cai et al. [59] presents ProxylessNAS, eliminating the need for proxy tasks by performing architecture search on target tasks and hardware directly. This process reduces accuracy drops due to bias in the proxy dataset. The method simplifies the NAS process and improves results.

H. Jin et al. [60] presents a method for efficient NAS called network morphism, where the architectures can increase; the method retains functionality. This method allows exploration of more complex models, and avoids retraining the model from scratch. This is helpful in efficient NAS techniques.

M. Tan and Q. V. Le [61] presents Efficient Net, introducing compound scaling to solve automatically balancing depth, width and resolution. With little manual tuning, the authors are able to achieve state-of-the-art performance with efficient models. Efficient Net's constructs influence NAS design methods.

X. Guo et al. [62] analyses reinforcement learning-based NAS methods, outlining policy gradient-based/search and evolving approaches. This review helps provide methods that researchers can follow as their NAS objectives and purposes vary in each application. This review enables researchers to see how an RL-based NAS strategy can help.

T. Elsken et al. [63] The authors present a mixture of Bayesian optimization and meta-learning for NAS that significantly reduces search cost associated with transfer learning. This process allows few-shot changes to architecture and increases efficiency of NAS. Bayesian optimization is shown to be a probabilistic model for NAS.

L. Xie et al. [64] A new hierarchical NAS performs semantic segmentation, searching the encoder-decoder structures jointly, optimizing the best architecture at different scales when searching. The hierarchical shows that by finding the right hierarchical features will improve the segmentation statistics which are optimizing the best hierarchical features.

L. Li et al. [65] This paper is a full survey of Neural Architecture Search (NAS). The authors summarize various methods based on the search strategy, evaluation methods, and search space. The authors also compared gradient, evolutionary, and reinforcement learning approaches. This survey is a foundational survey that provides a baseline for the taxonomy and success of NAS.

R. B. Zoph et al. [66] The authors propose a means of automating neural network architecture design using reinforcement learning (RL); specifically, they have a controller RNN that generates neural architecture. The RL controller is trained using policy gradients, and RL finds architectures that are superior to human designs for certain tasks, such as the CIFAR-10 tasks. This is one of the earliest and most impactful example of RL in NAS.

Y. Wang et al. [67] In this paper, APQ is introduced. It is a Unified framework for architecture search, pruning, and quantization. The authors optimize models for deployment, by formulating a joint optimization problem to find Pareto-optimal models, under hardware constraints. APQ is developed for edge devices, but the main contribution of the paper is showing benefits from using combined compression techniques with NAS.

J. Li et al. [68] The authors introduce GNAS a graph based neural architecture performance predictor. The goal of GNAS is to speed up NAS by being able to predict the performance of unseen architectures. This surrogate model significantly reduces the time spent searching for architectures while preserving accuracy. GNAS shows the potential of predictive modelling in making NAS more efficient and scalable.

Y. Xu et al. [69] This work uses reinforcement learning-based NAS in the image segmentation domain, optimizing the encoder and decoder portions of segmentation networks, and achieves similar results on established benchmarks, such as PASCAL VOC. This paper demonstrates that it is reasonable to extend NAS to structured output tasks, in contrast to more typical image classification tasks.

A. Krizhevsky et al. [70] This seminal paper presents Alex Net, a deep convolutional neural network that had substantial performance in the ImageNet classification challenge, using ReLU activations, dropout, and training on GPUs, which is an industry-leading application of deep learning research. Alex Net is a strong benchmark, and an important factor contributing to motivating automatic architecture search methods.

2.3 RESEARCH GAPS

While with great progress made to Neural Architecture Search (NAS) and its impact in Natural Language Processing (NLP) there exists a number of largely significant barriers that are impeding the full capability of it and are not easily accessible to everyone. Here are a couple of key hurdles:

1. **Poor Cross-Domain Generalization:** One subjective evaluation of the various NAS methods is that many execute accurately on certain tasks, i.e. natural language understanding, time series forecasting, dialogue systems, etc. But they often do not lend themselves very well to applications outside of their their area of success. There is great difficulty from applying successful architectures across domains, and the ease at which current NAS methods allow more appropriate variants to excel in their area of weak generalization is a major area of focus from research and engineering.

2. **Intuitive Language Interfaces:** Many NAS systems do not offer language modelling design tools that are very user-friendly and that do not cater to deep technical skills, stopping those less technical in their tracks. If natural language interfaces for modelling tasks were incorporated as an accessible aspect of the NAS process it would greatly improve usability and adoption of automated AI tools by many more people.

3. **Linguistic Limitations of Multilingualism:** Most NAS frameworks and evaluation benchmarks primarily apply to English-language-oriented tasks. We need language-independent tools that can effectively support multiple languages so that people of all backgrounds can equally benefit from model-generation tools.

4. **Computational Demands:** Although we have seen some improvements in the amount of computational power required, many NAS algorithms can still require a significant amount of GPU resources and long search times, making them realistically usable only by well-funded research and industrial use, hindering other experimentation and innovation.

5. **Interpretability:** Although NAS can find high-performing architectures, it is often not clear how the designed architecture came about. It is important to render these models more interpretable and transparent to allow for trust, easier debugging, and improved decision making when deploying these models.

If we can resolve these concerns, we can begin to make NAS and NLP advanced technologies, but more importantly, those that are easy and readily available for everyone.

CHAPTER 3
METHODOLOGY

3.1 INTRODUCTION

3.1.1 Objective of the Methodology

The purpose of this methodology is to create a user-friendly system, which can understand natural language task descriptions in many languages; and auto-generate the appropriate neural network architectures using AutoKeras. This methodology facilitates the deep learning model creation process by reducing the amount of manual programming required, and enables users to type the task description in natural language; creating a more intuitive way for users to specify their tasks. Ultimately, this methodology aims to enable as many machine learning tasks as possible in any domain; and provide people with advanced technology, which is usually reserved for experts.

3.1.2 Overview of the system

The proposed system provides a unique mechanism that combines natural language processing (NLP) and automated neural architecture search to decentralize the usability of deep learning models. The user can too easily convey their machine learning tasks in natural language - "text classification" or "Please create a regression model with dropout" - and the system identifies the task from the user's request and understands exactly the types of components are required to understand it (the components of the model configuration in this case). These elements consist of: number of layers, types of layers, and activations. Designed with a view to inclusivity, this natural language interface enables users to use multiple languages, allowing for a wider pool of subject matter expertise and technical familiarity from users of many different technical backgrounds allowing them to engage effectively with the system and make use of the system's capabilities. In other words, this type of approach reduces barrier for entry in building a model using machine learning technologies and creates a level playing field of accessibility to machine learning technologies.

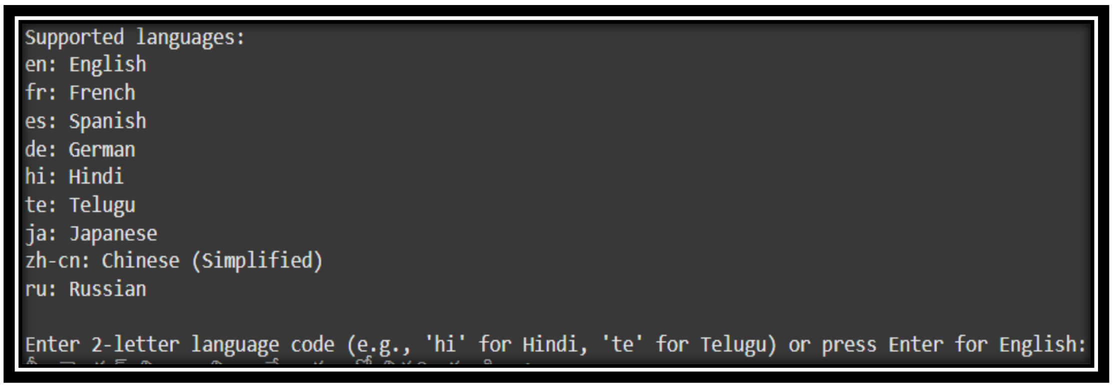
Once we have established the requirements of the task, the system will convert the information into a format that is structured and compatible with AutoKeras. AutoKeras will then take over and fully implement the rest—all the user needs to do is select the desired model and train it (AutoKeras will build the model, optimize it and evaluate its performance). The generated architecture is appropriately technical, but also relevant to the user's needs and the task's specifics. Also notable is the language of the model description: the model description is in a language the user chooses, which contributes to greater clarity and usability. This approach takes deep learning and makes it more user-friendly, reducing technical hurdles, and facilitating the use of deep learning across disciplines.

3.2 NLP PROCESSING ENGINE

3.2.1 Natural Language Input

As part of the proposed system, to improve user experience, natural language input and output in several languages is supported, to facilitate accessibility for individuals from different linguistic backgrounds. At the beginning of the interaction, the users are asked to choose the language they would like to use in communications. The speech act must create a requirement for the language to be selected and once the users select the language, all the other inputs will be processed in that language, and the system will respond in that language so as constitute a seamless and personalized experience for each user.

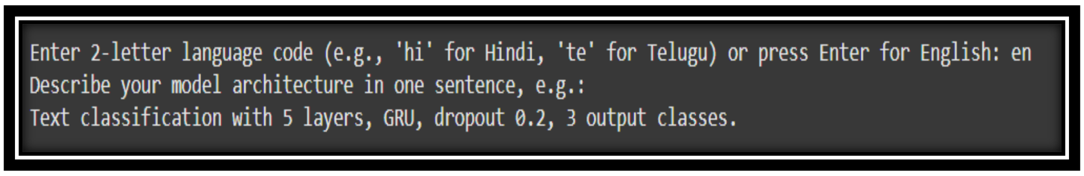
To show this capability, we've included screenshots that demonstrate the system's ability to accept input in two different languages. This highlights not only its support for multilingual use but also its capacity for real-time adaptation.



```
Supported languages:
en: English
fr: French
es: Spanish
de: German
hi: Hindi
te: Telugu
ja: Japanese
zh-cn: Chinese (Simplified)
ru: Russian

Enter 2-letter language code (e.g., 'hi' for Hindi, 'te' for Telugu) or press Enter for English:
```

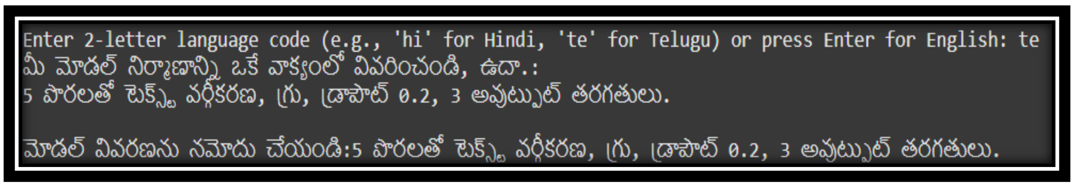
Figure 3.1: Language Support for Input and Output

- ➢ This prompt asks the user to choose their language for communication, allowing the system to process all further input and outputs in the chosen language to provide a tailored experience that feels seamless.



```
Enter 2-letter language code (e.g., 'hi' for Hindi, 'te' for Telugu) or press Enter for English: en
Describe your model architecture in one sentence, e.g.:
Text classification with 5 layers, GRU, dropout 0.2, 3 output classes.
```

Figure 3.2: User Input in English Language



```
Enter 2-letter language code (e.g., 'hi' for Hindi, 'te' for Telugu) or press Enter for English: te
మీ మోడల్ నిర్మాణాన్ని ఒకే వాక్యంలో వివరించండి, ఉదా.:
5 పొరలతో టెక్స్ట్ వర్గీకరణ, గ్రు, డ్రాపౌట్ 0.2, 3 అవుట్పుట్ తరగతులు.

మోడల్ వివరణను నమోదు చేయండి:5 పొరలతో టెక్స్ట్ వర్గీకరణ, గ్రు, డ్రాపౌట్ 0.2, 3 అవుట్పుట్ తరగతులు.
```

Figure 1.3: User Input in Telugu Language

- When a user selects a preferred language, the system changes its understanding and response to make sure all the interactions are in this preferred language as smoothly as possible

3.2.2 Task Type and Parameter Extraction

Once we have analyzed the natural language input to extract what task was requested, our system recognizes the task type and extracts the corresponding model configuration parameters needed to set the neural network architecture for that task. Right now, we only support five machine learning tasks:

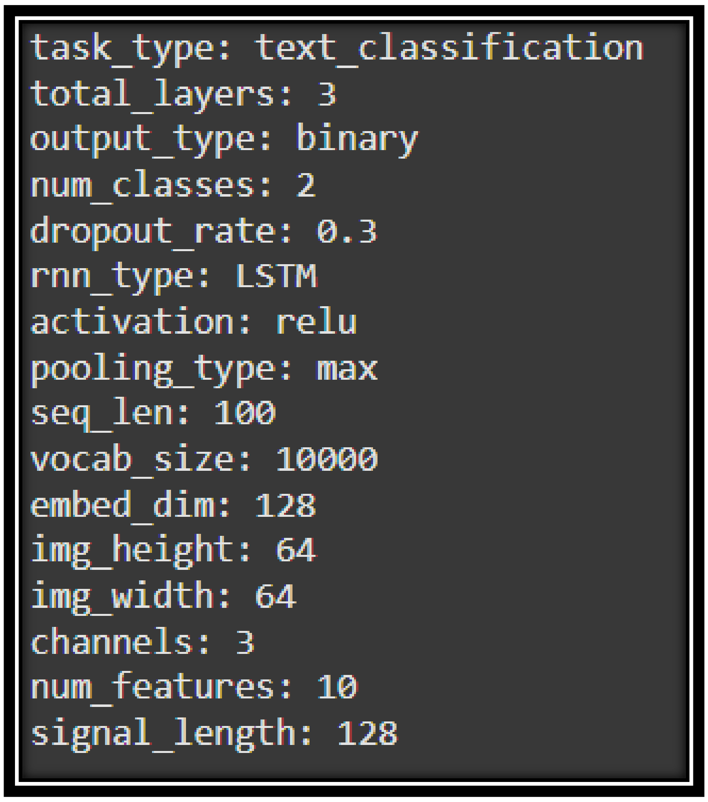
(1) Text Classification
(2) Time Series Forecasting
(3) Regression
(4) Sentiment Analysis.
(5) Image Classification.

These tasks each have specific parameters that drive the architecture design so we are able to produce custom solutions tailored for the unique aspects of each project. The system extracts relevant parameters that were explicitly mentioned in the user request. These parameters support the model architecture and hyperparameter selection.

The following are the parameters we have the capability to extract from the natural language input:

- **total_layers:** Total number of layers in the architecture
- **output_type:** Nature of output (e.g., binary, multiclass)
- **num_classes:** Number of target classes
- **dropout_rate**: Dropout rate to prevent overfitting
- **rnn_type:** Type of recurrent layer (e.g., LSTM, GRU)
- **activation:** Activation function (e.g., ReLU, Sigmoid)
- **pooling_type:** Pooling method (e.g., max, average)
- **seq_len:** Input sequence length (for text or time series tasks)
- **vocab_size:** Vocabulary size (for NLP tasks)
- **embed_dim:** Embedding dimension for text input
- **img_height:** Height of input images
- **img_width:** Width of input images
- **channels:** Number of image channels (e.g., 3 for RGB)
- **num_features:** Number of features in tabular data
- **signal_length:** Length of the input signal (for time series tasks)

If a user omits any necessary parameter from the user input, the system will set a default value to the parameter for the task type and what is generally accepted. This ensures that the generated model configuration will represent a complete model configuration for downstream processing.



```
task_type: text_classification
total_layers: 3
output_type: binary
num_classes: 2
dropout_rate: 0.3
rnn_type: LSTM
activation: relu
pooling_type: max
seq_len: 100
vocab_size: 10000
embed_dim: 128
img_height: 64
img_width: 64
channels: 3
num_features: 10
signal_length: 128
```

Figure 3.2: Predefined Input Values

This parameter extraction and defaulting functionality allows users to focus on the details, they recognize or care about, while the system manages any aspects that are necessary for the configuration, the system is managing those quite adequately. In this manner, we are able to really make the model creation process simple for the user, and therefore we can be up front, and efficiently useful.

3.2.3 NLP Workflow

When a user provides their input, a structured Natural Language Processing (NLP) workflow is initiated that is meant to analyze and interpret their input before mapping it into a format that machines can "understand." In summary, the major goals for this workflow are to analyze the natural language descriptions, classify the type of machine-learning task the user intends (e.g., classification, regression, or forecasting), and identify the key architectural parameters (e.g., number of layers, types of recurrent units (e.g., LSTM, GRU), dropout, activation functions, input dimensions, etc.) required for running the model while iteratively refining the natural language task into key parameters.

The workflow starts with analysing the sentences and then uses keyword identification to classify the type of task, such as classification, regression, or classification. After determining the type of task involved, the system will request other important configuration items from the user, like the number of layers, types of recurrent units (e.g., LSTM, GRU), dropout, activation functions, input dimensions, etc. After parameters had been identified, they will be summarized into a structured format used as "input" for the automated model generation pipeline.

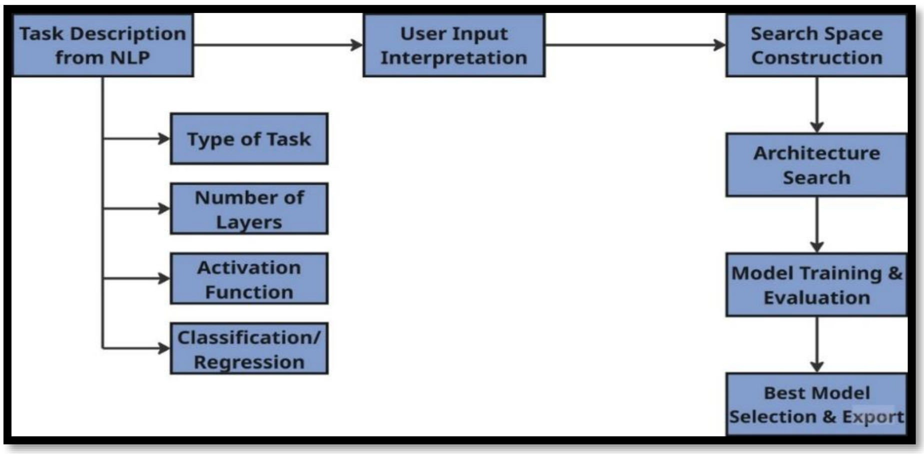

Task Description from NLP
User Input Interpretation
Search Space Construction
Type of Task
Number of Layers
Activation Function
Classification/ Regression
Architecture Search
Model Training & Evaluation
Best Model Selection & Export

Figure 3.3 : Workflow of NLP System

If any critical parameters are missing from a user's input, the system will automatically fill in the gap with default values. In this manner, there is uniformly a complete and valid configuration for model construction. This allows for more flexible user experience and ultimately strengthens the interaction's robustness.

3.3 AutoKeras Integration

3.3.1 Summary of AutoKeras Connection

AutoKeras is a new open-source AutoML framework that runs on Keras. Its purpose is to reduce the barriers that machine learning practitioners will have in developing deep-learning models by removing some of the challenges associated with architecture search and hyperparameter tuning. By utilizing powerful Neural Architecture Search (NAS) methods AutoKeras will also remove many of the hurdles associated with exploring and searching the many configurations provided by a deep-learning architecture. In this sense AutoKeras simultaneously saves time, and reduces the expertise required to develop a high-quality neural network allowing many more people to use deep learning.

By including AutoKeras, the system creates an open and understandable link between the primacy of the users natural language intentions for the deep learning model, with the murky development factors regarding their model. It tells a single, understandable story for machine learning that is easy for regular people to understand and scalable so they can communicate a ton of stuff (like image and text classification, time series forecasting, regression, and sentiment analysis). For example, using the automated functions of AutoKeras, people can easily and quickly deploy optimized models with minimum manual intervention, thus making the expectations of machine learning less fuzzy and less work.

3.3.2 AutoKeras Workflow

AutoKeras takes the structured configuration from the NLP module and converts it into an applied deep learning model.

AutoKeras does so based on a workflow that systematically takes user input, processes and recognizes it, and assembles it into an optimal neural network architecture with respect to its mapped dataset and type of machine-learning task.

1. Processing User Input and Recognizing Task

The system starts by accepting structured input such as task category, layer types, and activation functions. During this first stage, processing the structured input brings the task for the machine learning and structure to be recognized, which constitutes the task and thus informs AutoKeras' decision in architectural choices.

2. Mapping and extracting for parameter information

The input terms that were rendered user-friendly are mapped to technical names / definitions as they are noted in a dictionary in digital space. The system then extracts layer types, and activation functions being careful to extract the specific type respective to AutoKeras components.

3. Assembling meaningful Configuration

Once all parameters have been extracted and mapped, they will be compiled into a single configuration object with the default value parameters mapped in a configuration panel. For parameters not extracted at all, or just not specified in the configuration option then defaults are used, which will integrate uniformity to the model generation process..

4. Automated Model Generation

We have now established a configuration structure and we can begin to allow AutoKeras to more effectively search the architecture space in its many layers and hyperparameters.

AutoKeras will continue to create, test, and evaluate every candidate model until every last candidate has been produced

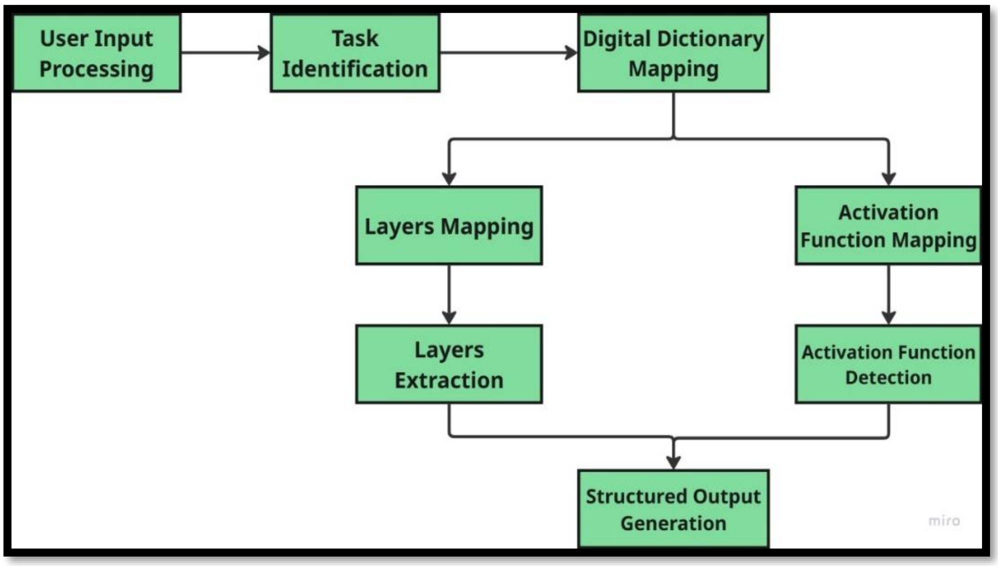

User Input Processing
Task Identification
Digital Dictionary Mapping
Layers Mapping
Activation Function Mapping
Layers Extraction
Activation Function Detection
Structured Output Generation
miro

Figure 3.4 : AutoKeras Model Building Workflow

and evaluated. AutoKeras will then choose the model (best performing one) and produce a complete model architecture that can be trained or tuned further.

➢ Thus, one could consider AutoKeras as a backend engine that encodes what the user is wanting to do, with the highest quality deep learning potential, to allow model building with a minimal overhead of manual work.

3.4 SYSTEM WORKFLOW

3.4.1 Processing User Inputs

Processing of user inputs is a fundamental Mahihin step in the process workflow for our system. This is where we collect the user input data needed to build a neural network model. We have identified ways to efficiently and effectively develop models through model creation and used two compulsory inputs and options to allow user customization to meet a variety of needs.

Compulsory Inputs:

1.Task:

Firstly, you will need to state the main machine learning task you want to perform; for our examples this will be either classification or regression. This first input is the beginning of the model building process to determine how to construct the best modelling strategy for your problem.

2.Task Type:

Once the user has selected the task type, we will then need to select what task they are doing or completing, such as, binary classification, multi-class classification or multi-label classification. Task type is an important consideration, as they will drive how we can better align model structure and training objectives to their needs.

Optional Inputs:

1. Dataset Upload:

You may upload a custom dataset for your task. Our system will evaluate your uploaded dataset to ensure that the format and content align with your uploaded specifications. If you decide not to upload a dataset, do not worry-- a pre-configured default dataset that fits your task grid will be used. You are able to continue generating and evaluating the model as expected.

2.Model Hyperparameters:

You may choose various model hyperparameters, like layers, dropout rate, activation functions, layer types, etc. This option allows you to customize the neural network architecture based on your preferences, especially if you have experience in the domain. If you choose not to, the system will use default values for the parameters and use AutoKeras to perform the neural architecture search with the default settings to find the best values for your project.

Combining important task information with flexible optional parameters is a balance between usability and customization, allowing an array of users to easily generate models fit to their needs and specific applications.

3.4.2 Model Generation and Optimization

The Model Generation and Optimization stage is key to the system's functionality. This stage converts user-provided natural language instructions into a full, optimized deep learning architecture. This stage is developed in such a way that it is highly automated and easy to use, catering to users with little machine learning experience, yet highly customizable for experienced users.

The stage utilizes a two-stage pipeline; it first uses Natural Language Processing (NLP) to process the user input and then AutoKeras, which encapsulated the process of neural architecture search and model optimization. This approach allows users with multiple levels of expertise to fully utilize the technology to suit their needs.

Natural Language Processing (NLP)

The first step in the model generation pipeline uses Natural Language Processing (NLP) to interpret user input appropriately. NLP is a critical component in the conversion of unstructured text created by users into structured knowledge. NLP establishes the primary task to be generated (classification or regression) and identifies the task type (binary, sink, or multi-class classification). Additionally, it collects the user's settings such as the number of layers, layer return functions, dropout rates, type of layers, etc.

The process is completed with a collection of approaches including but not limited to rule-based recognition of patterns, finding keywords (i.e. rule-based matching), and including a structured parse. The output is then validated and standardized into an internal organized configuration, structured so that if the user is entering ambiguous or disorganized language, the NLP will transform that input into clear instruction for the model generator. Specifically, the NLP module is a hop between the natural expression from the human user and the command for the machine to act on; the way in which the user understands their tool, and how the material acts on the technology is to be more intuitive.

AutoKeras Integration

After the user input has been converted to a structured format, it is sent to the AutoKeras engine. AutoKeras is a free and open-source AutoML system build on Keras, which was developed to make the development and optimization of deep learning models easier via Neural Architecture Search (NAS). AutoKeras will use the interpreted user input to search it's search space and build the model architecture based on the type of task that the user input and any user constraints.

When users provide some constraints over certain architecture components (types of layers, number of layers, activation functions) AutoKeras will allow these components in the search space. If users decide not to specify any of these components, AutoKeras will autonomously make design decisions and selections on the best configurations based on trials and performance measures. The framework will completely automate the various training, validation, and hyperparameter selections of the various trials/interactions and produce an optimal model with minimal user effort.

The process of model generation and optimization blends advanced language understanding with automated deep learning techniques to create a user-friendly system that simplifies neural network design for everyone. By integrating the interpretive capabilities of natural language processing (NLP) with the intelligent search functions of AutoKeras, this system enables users to generate high-quality, task-specific models with ease. This approach not only makes the technology more accessible for beginners but also empowers experienced users with the flexibility and power they need, making it possible to tackle a wide range of machine learning applications efficiently and effectively.

3.4.3 Workflow Diagram and System Architecture

In this section, you will view an illustration of the full workflow of our system, taking you through a user initiated event all the way to a model output. The image below illustrates how a user interface connects with an NLP engine, connects with a data set interface, and collaborates with an AutoKeras optimizer to automate the generation and tuning of our neural networks.

As shown in the image below, we have depicted the flow of all operations taking place within the system. The connectivity of how natural language originates into structured configurations later with optional data set handling, to the linking back of AutoKeras that automates the model improvement in leasing production efforts. The progress of this stage of development is embedded into this precise depiction of cross functionality combined with the enhanced function of Neural Architecture Search.

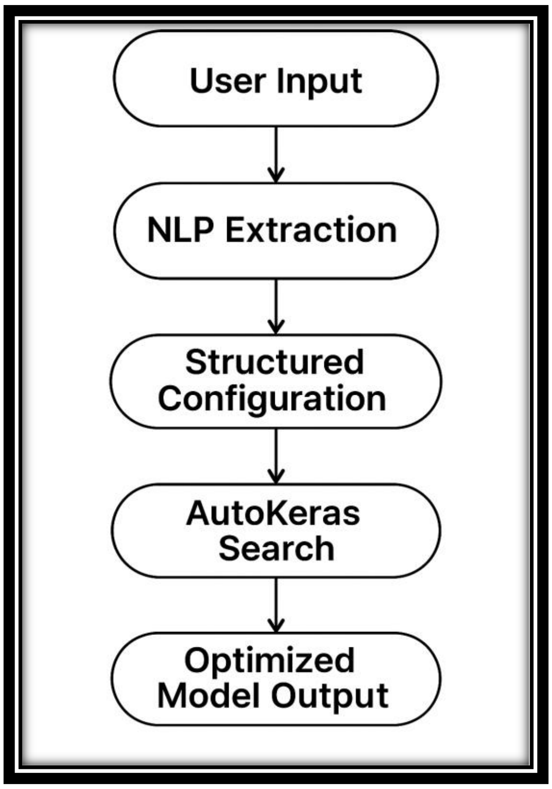


Figure 3.5 : NLP-Based AutoKeras Workflow

The process depicted in the image illustrates how the NLP module interfaces with AutoKeras, an efficient way for the user to receive Neural Architecture Search (NAS) to build the best model possible within the constraints of their data. When a user provides a dataset, it is validated and processed; if the dataset turns out invalid, then a reasonable choice is made to work with a default dataset. AutoKeras even smartly makes choices (like determining layer types or activation functions) when the user simply does not share those iformation. In the final step, the system has trained and evaluated a range of architectures, then picks the best performing architecture based on a performance metric. The system has also other optional parts like logs, visualizations and translated summaries to promote user understanding, establishing a user journey from basic natural language input to an optimized deep learning model.

3.5 SUMMARY

This project proposes a new way to build a system that utilizes NLP and AutoKeras to simplify the construction of deep learning models. The system enables users to describe their needs in natural language, allowing the system to obtain relevant parameters from their needs, and ultimately automating the creation of custom neural architectures. The system can take user's input in many languages (they can use language of their choice) and as a whole takes care of their needs by using the NLP component to convert their needs into a process it can understand, while allowing AutoKeras to search for the appropriate architecture and hyper paremeters - minimizing user's work where possible.

At the end of the day, this system improves model creation with improved efficiency and scale in different uses cases (that include, among others): image classification, text classification, time series forecasting, regression, and sentiment analysis. The systems modularity and ability to automate things of greatest utility will make it useful for both novice and expert actioners looking to strengthen their work flowing deep learning.

Chapter 4
Results and Discussion

4.1 EVALUATION METRICS

In this project, we will evaluate two key areas in our project—the interpretation of the natural language task descriptions, and the quality of the neural network architectures that were generated. Since our system combines natural language processing and automated architecture generation, our evaluation plan emphasizes modules of evaluation surrounding functional correctness, language understanding, and user-friendly design.

4.1.1 Natural Language Understanding/Interpretation

The system enables users to describe machine learning tasks in multiple languages, and our evaluation focuses on three key areas:

- **Accuracy of Task Recognition:** We will closely observe if the system recognizes the intended task that is described by the user in their input. For instance, our users will describe a task as 'text classification' or 'regression.' The system should able to identify that user is describing a task.
- **Extraction of Architectural Parameters:** We also want to ensure the system understands essential parameters. For example, the correct layer types, number of layers, dropout rates, and output classes are represented in the configuration generated by the system.
- **Multilingual Robustness:** We want to evaluate, and how reliably the system is representing, information across

several languages to ensure our system is flexible and usable for users who speak several different languages.

Most of our evaluations will be qualitative in nature, where we will conduct many tests with many different natural language inputs. We will ensure our system outputs are the same thing that the users think they are, which allows them to have the same experience without any disruption.

4.1.2 Quality Quality of Generated Architectures

The generated neural network architectures should be evaluated for the following:

- **Structural Validity:** The architectures are within the AutoKeras restrictions, run without error to ensure robustness in model selection and use.
- **Task Validity:** The configurations complete the user's intended tasks and used appropriate and informed layer types and structural components to maximize model performance.
- **Understandability and Utility:** The model specifications advanced and contained in the description are in the user's language and contained clear comparisons/clarifications to provide more understanding and useful purposes for using the generated architectures.

These criteria help ensure that the models we generate are not only technically proficient but also meet the needs of users. By verifying the structure, suitability for specific tasks, and clarity, the system delivers neural architectures that are both reliable and easy to understand. This approach supports smooth implementation and promotes user engagement across a wide range of applications.

4.1.3 Summary

Through the thoughtful combination of natural language understanding and dependable architecture creation processes, our assessment strategy exists to ensure the system produces meaningful and useful outputs which meet user needs. Not that we are going to stress formal quantitative measures at this point but our qualitative assessments of architecture generated out of numerous multilingual inputs and architecture assessments clearly demonstrate the system's development and rigor.

4.2 PERFORMANCE COMPARISON

4.2.1 Overview of Methods for Generating Architectures

Neural architecture generation is an important aspect of simplifying deep learning processes. We have seen an increase in user-friendly AI products, such as AutoML frameworks (e.g., AutoKeras and NASNet), and transformer models (BERT and GPT) allowing less technical users to carry out the complexities of designing neural networks. Each of these methods has advantages and disadvantages depending on the specific task and the degree of automation required.
In our project, we want to provide the ability for users to describe their tasks in natural language, allowing for the automatic generation of the best neural architectures for them. This requires a framework that can take a variety of machine learning tasks, use natural language processing interfaces, and offer significant automation.

4.2.2 Other Ways to Generate Neural Architectures

1. **AutoKeras (AutoML-Based NAS):** AutoKeras works to automate the entire workflow of: data preprocessing, architecture search with hyper-parameter fine-tuning, model training, and model prediction. Further, AutoKeras demonstrates its "user friendly" nature by its scalability to different types of data without a need for recompiling the tools. This flexibility makes AutoKeras particularly useful for projects including natural language processing (NLP).

2. **BERT (Bidirectional Encoder Representations from Transformers):** The BERT model can be identified as potentially the most powerful pre-trained model used for language understanding that has had a significant impact on the machine learning domain. BERT is identified as a useful method to understand and exploit the intricacies of the contextual relationship of language with its many different applications. For example, it does exceptionally well with NLP classification and question answering applications. However, BERT itself does not generate automatic architectures. Also note, customizing BERT for different applications can be even more laborious than generating a simple model.
3. **GPT (Generative Pre-trained Transformer):** The GPT language model has the ability to tackle different tasks associated with natural language generation and natural language processing with great effectiveness. Although the effectiveness persists without other customization, reliance on customizations or prompt engineering can diminish using GPT for searching large scale neural architectures.

4. **NASNet (Neural Architecture Search Network):** NAS Net uses reinforcement learning to discover efficient convolutional neural network (CNN) architectures. It mainly has applications in vision tasks. The method is computationally intensive and requires tuning of the controller manually which prevents the method from being applied by many users.
5. **ENAS (Efficient NAS):** ENAS builds upon traditional neural architecture search methods by weight sharing to be more efficient. It still requires a certain level of technical knowledge to define the search spaces and controllers so it may be limited for those new to the area.
6. **DARTS (Differentiable Architecture Search**): DARTS is applicable to area of research where gradients can be used to replace methods of discrete search with continuous optimization. DARTS is more efficient than some of the other traditional methods but it can still be a complex technical solution and does not natively support input that is NLP focused or general tasks.

4.2.3 Justification for Selecting AutoKeras

AutoKeras is the best candidate for our platform built around the generation of neural architectures intended for natural language processing; it has a unique feature set that aligns well with our intentions

- ➢ AutoKeras builds the entire model with the best architecture for the user task automatically with imputed manual effort.
- ➢ AutoKeras accepts many data types—image, text, tabular, and time series—and can operate in many different real-world applications.

- AutoKeras has a natural language input, which means the user can describe task in plain language for a more intuitive interaction.
- AutoKeras is low-code open-source platform that provides low-tech barriers, which means users may not need to possess extensive coding experience to make use AutoKeras to manufacture their own AI application
- AutoKeras is scalable and flexible, indicating it has strong performance across multilingual and domain-agnostic settings for research or production.

Unlike traditional transformer models, such as BERT and GPT, which have a prescribed architecture to support a specific task without deviations, AutoKeras affords a more agnostic and universal way to build models. Using descriptions of language-based tasks, incorporating a level of automation, and handling multi-modal data types, AutoKeras provides us with the scaffolding needed to build how the architecture of our system.

4.3 RESULTS AND OBSEVATIONS

4.3.1 Evaluation Objective

To assess how adaptable and optimized our system is, we have tested natural language natural inputs in multiple various languages and analyzed the resultant model descriptions. The results demonstrate our systems ability to process multiple languages, respond to natural language processing and derive an accurate architecture from Autokeras.

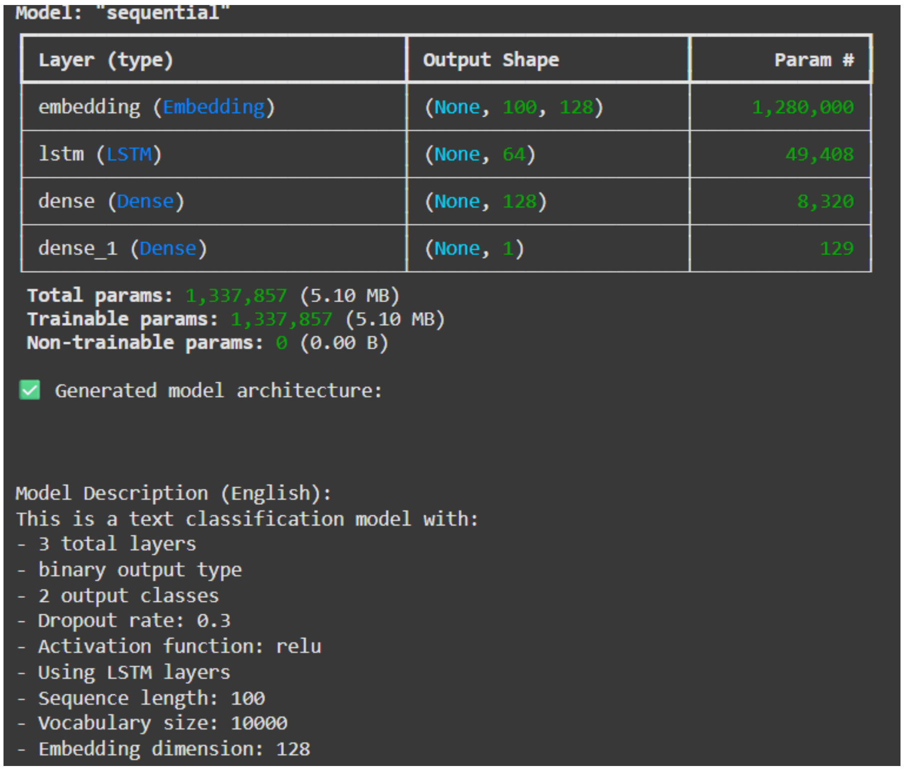
4.3.2 Multilingual Task Input and Output Generation

This section provides more examples of how users can articulate machine learning tasks in different languages. The intent of this section is to showcase the systems understanding of such descriptions and its ability to produce appropriate details of model architecture, in the same language, or translated to another.

- **Example 1 – English Input & Output**

  Input: "Build a text classification model."

  Output: A detailed model configuration for text classification generated and explained in English



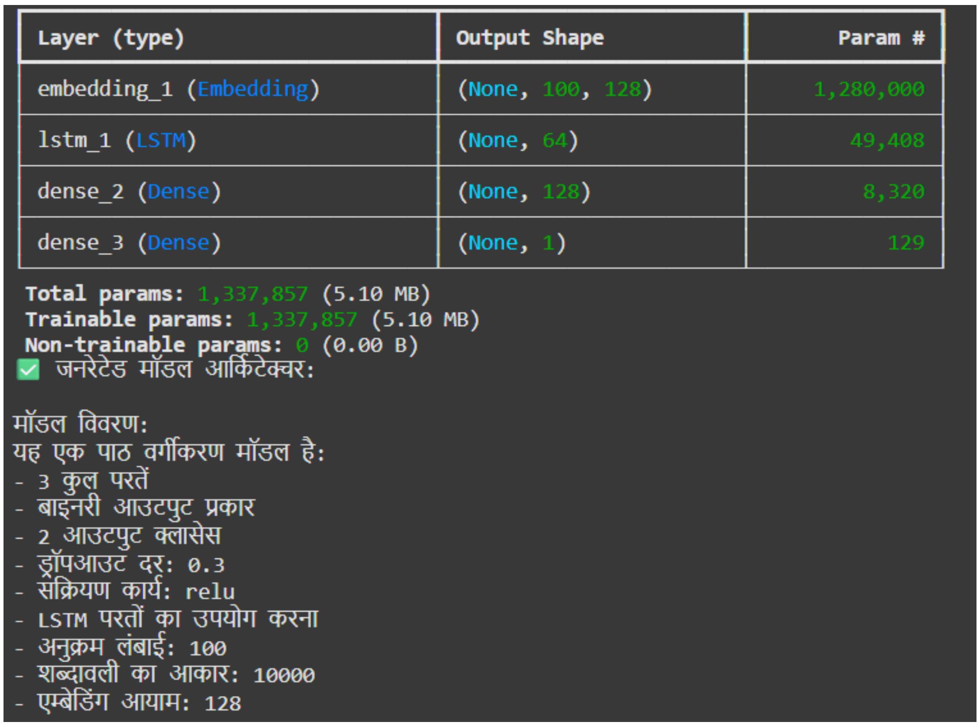
```
Model: "sequential"
┌──────────────────────────────┬─────────────────────┬───────────┐
│ Layer (type)                 │ Output Shape        │   Param # │
├──────────────────────────────┼─────────────────────┼───────────┤
│ embedding (Embedding)        │ (None, 100, 128)    │ 1,280,000 │
├──────────────────────────────┼─────────────────────┼───────────┤
│ lstm (LSTM)                  │ (None, 64)          │    49,408 │
├──────────────────────────────┼─────────────────────┼───────────┤
│ dense (Dense)                │ (None, 128)         │     8,320 │
├──────────────────────────────┼─────────────────────┼───────────┤
│ dense_1 (Dense)              │ (None, 1)           │       129 │
└──────────────────────────────┴─────────────────────┴───────────┘
 Total params: 1,337,857 (5.10 MB)
 Trainable params: 1,337,857 (5.10 MB)
 Non-trainable params: 0 (0.00 B)

✅ Generated model architecture:


Model Description (English):
This is a text classification model with:
- 3 total layers
- binary output type
- 2 output classes
- Dropout rate: 0.3
- Activation function: relu
- Using LSTM layers
- Sequence length: 100
- Vocabulary size: 10000
- Embedding dimension: 128
```

Figure 4.1: English Input to Neural Architecture Output

- **Example 2 – Hindi Input, Hindi Output**

  Input: "एक टेक्स्ट वर्गीकरण मॉडल बनाएं।"

Output: Architecture output and explanation correctly displayed in Hindi to demonstrate multilingual use.



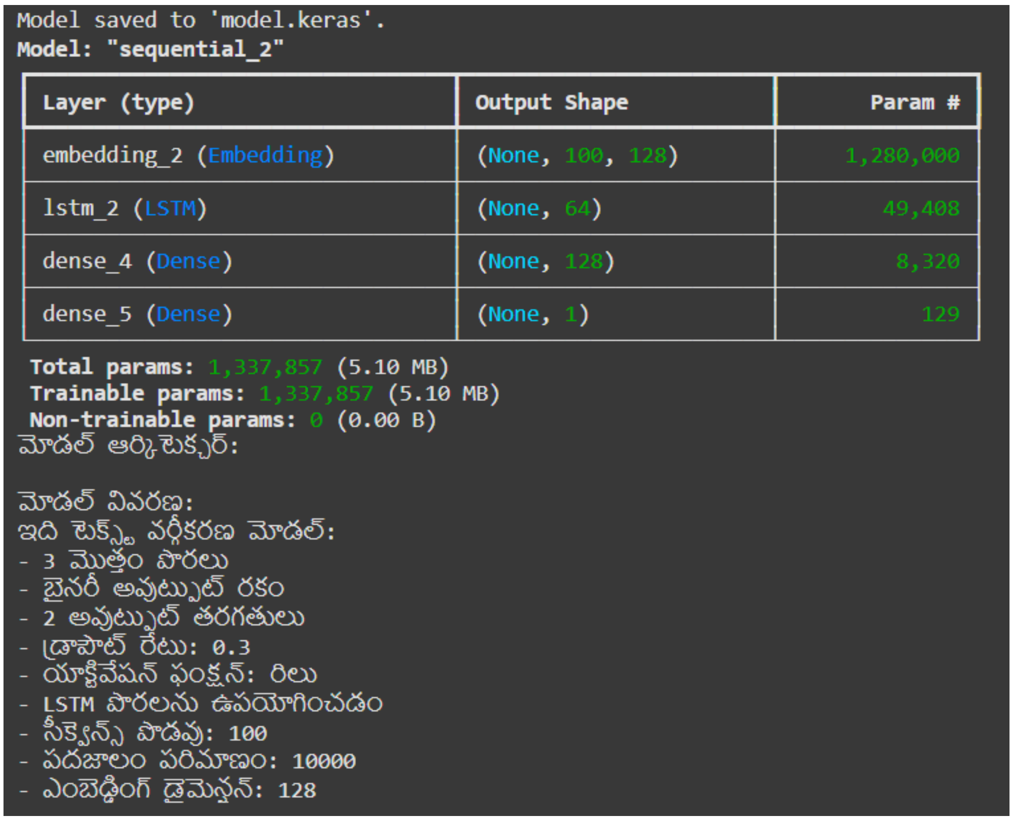
```
Layer (type)                  Output Shape           Param #
embedding_1 (Embedding)       (None, 100, 128)     1,280,000
lstm_1 (LSTM)                 (None, 64)              49,408
dense_2 (Dense)               (None, 128)              8,320
dense_3 (Dense)               (None, 1)                  129

 Total params: 1,337,857 (5.10 MB)
 Trainable params: 1,337,857 (5.10 MB)
 Non-trainable params: 0 (0.00 B)
✅ जनरेटेड मॉडल आर्किटेक्चर:

मॉडल विवरण:
यह एक पाठ वर्गीकरण मॉडल है:
- 3 कुल परतें
- बाइनरी आउटपुट प्रकार
- 2 आउटपुट क्लासेस
- ड्रॉपआउट दर: 0.3
- सक्रियण कार्य: relu
- LSTM परतों का उपयोग करना
- अनुक्रम लंबाई: 100
- शब्दावली का आकार: 10000
- एम्बेडिंग आयाम: 128
```

Figure 4.2: Hindi Input to Neural Architecture Output

- **Example 3 – Telugu Input, Telugu Output**

Input: 5 పొరలతో టెక్స్ట్ వర్గీకరణ, గ్రు, డ్రాపౌట్ 0.2, 3 అవుట్పుట్ తరగతులు.

Output: System generated model description for text-classification in Telugu.



```
Model saved to 'model.keras'.
Model: "sequential_2"
┌─────────────────────────────────┬────────────────────────┬───────────────┐
│ Layer (type)                    │ Output Shape           │       Param # │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ embedding_2 (Embedding)         │ (None, 100, 128)       │     1,280,000 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ lstm_2 (LSTM)                   │ (None, 64)             │        49,408 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_4 (Dense)                 │ (None, 128)            │         8,320 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_5 (Dense)                 │ (None, 1)              │           129 │
└─────────────────────────────────┴────────────────────────┴───────────────┘
 Total params: 1,337,857 (5.10 MB)
 Trainable params: 1,337,857 (5.10 MB)
 Non-trainable params: 0 (0.00 B)
మోడల్ ఆర్కిటెక్చర్:

మోడల్ వివరణ:
ఇది టెక్స్ట్ వర్గీకరణ మోడల్:
- 3 మొత్తం పొరలు
- బైనరీ అవుట్పుట్ రకం
- 2 అవుట్పుట్ తరగతులు
- డ్రాపౌట్ రేటు: 0.3
- యాక్టివేషన్ ఫంక్షన్: రిలు
- LSTM పొరలను ఉపయోగించడం
- సీక్వెన్స్ పొడవు: 100
- పదజాలం పరిమాణం: 10000
- ఎంబెడ్డింగ్ డైమెన్షన్: 128
```

Figure 4.3: Telugu Input to Neural Architecture Output

4.3 SUMMARY

The experimental results have shown exactly how flexible and adaptable this proposed system is. By permitting description tasks in more than one language and transforming tasks to specification of network via the neural network configuration, the system combines natural language processing to AutoKeras. This broadens functionality and provides levels of inclusive innovation and accessibility.

Our testing in multilingual testing shows that our project could handle a broad range of inputs, while accurately outputting the correct model. The automated pipeline process allows architectures to be generated with ease. Bringing in the outsiders with little or no technical knowledge, so they do not feel anxious and overwhelmed through the stages of interaction and engaging the system's capabilities. The results provide implications of the overall usability, accessibility and scalability for the proposed means to a whole range of domain areas and user expertise.

Chapter 5
Conclusion and Future Scope

5.1 CONCLUSION

This project aims to produce an easy-to-use system that allows people to build deep learning models with much less hassle. It makes it possible for a person to express exactly what they want using simple, everyday language, without the complicated programming that goes with it, in the traditional sense. The unique combination of Natural Language Processing (NLP), with the AutoKeras framework for automatically performing hyperparameter optimization of neural networks based on a specific task, enables the system to understand what a user wants and automatically generate and optimize a neural network based on the user's simple and casual language. By providing a much-simplified approach to the entire model-creating process, by eliminating the traditional hurdles faced by the user, this opens up access to advanced AI technologies, and the world of deep learning, to a wider section of users.

5.2 FUTURE SCOPE

The existing system provides an effective way to automate the construction of neural networks using natural language. However, there are several strategic enhancements that would improve the system's usability and appeal. Here are a few future directions that detail several key areas of improvement:

1) **Support for Large-Scale Datasets:**
   Currently, the system functions relatively well with standardized, benchmark datasets but is very limited in its ability to handle

larger data types common in areas like healthcare and finance. Developing better strategies for memory optimization, batch-wise streaming, and distributed training should lead to some enhancements for neural networks built for data-heavy tasks.

2) **Voice Activated Input:**

Users can now enter tasks via text, but voice-activated or voice-recognition input is a good future enhancement that would make it easier for more users to access the system. This would especially be useful for non-technical users or in a hands-free environment. With speech recognition and language understanding modules, task descriptions can be converted from spoken language to be treated identically as written or typed text.

3) **Cross-Domain and Multimodal Expansion**

Presently, the system is confined to domains that contain a singular type of data, such as NLP or image classification. By expanding the capability of the system in the future to support multimodal tasks—which contain a text, image, or audio input—would increase the flexibility of the system. This would be particularly useful in areas like medical diagnostics or multimedia analysis, where combining different data types often leads to more effective task performance.

4) **Improved Model Interpretability**

While the system produces usable architectures, it is often unclear to users how and why a model was selected. Developing visualizations and layer-by-layer explanations will improve transparency, lead to better decision-making, allow users to obtain greater trust in their models and is especially useful for learners and non-experts.

5) **Apply & Test in Real-Time**

Currently, users receive the model architecture, but functionality testing is originated outside that functionality. Allowing users to validate, and test, in one click via a (cloud-based) local environment would speed up the validation and iterative testing processes, making the tool more useful for user-imposed, quick development, prototyping, etc.

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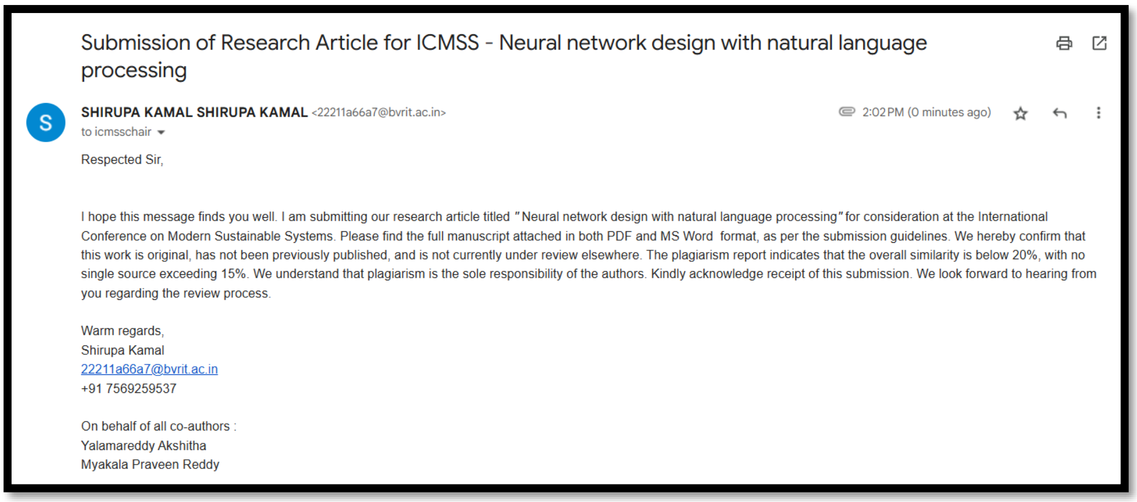

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SHIRUPA KAMAL SHIRUPA KAMAL <22211a66a7@bvrit.ac.in>
to icmsschair

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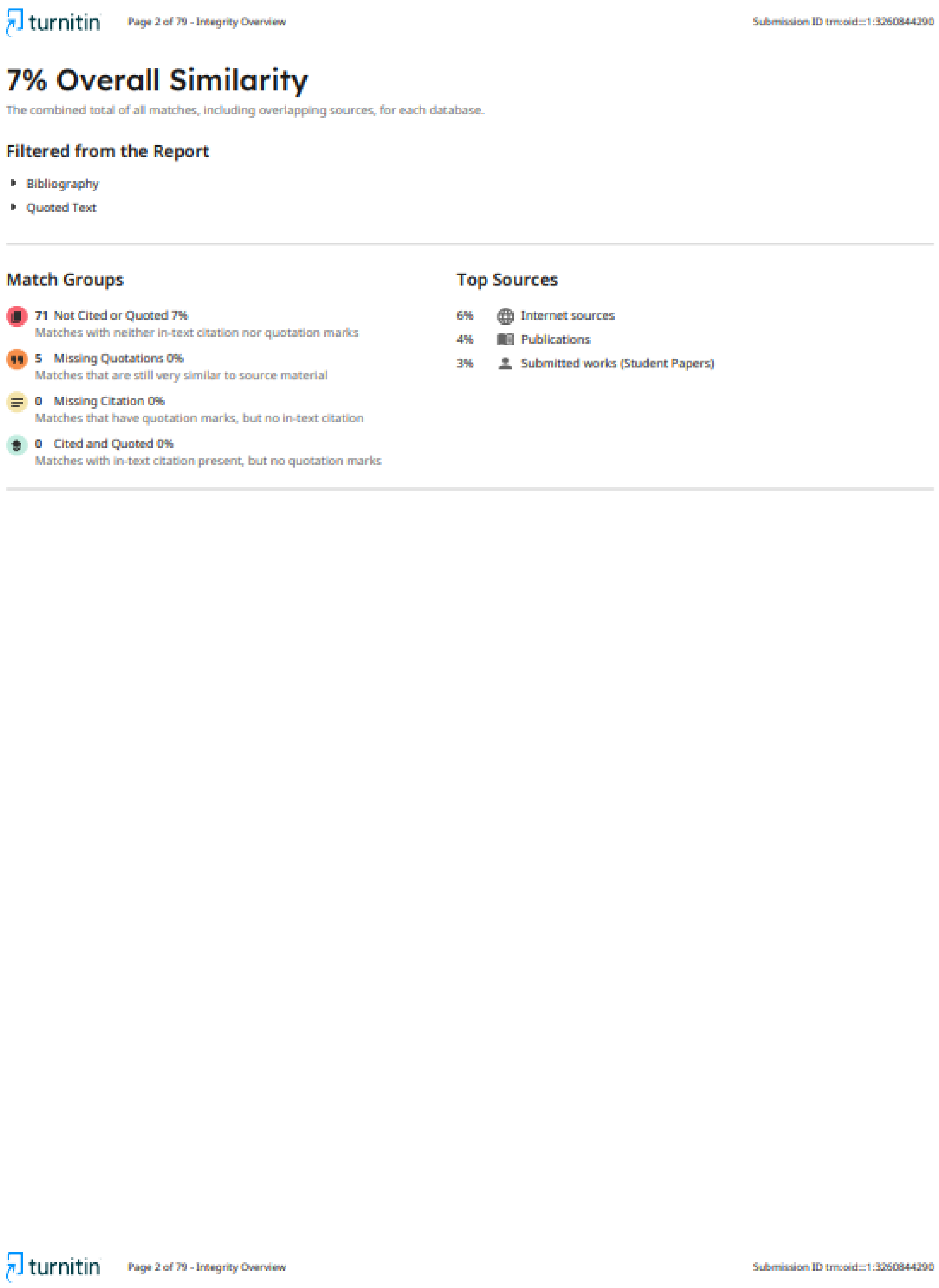
PLAGIARISM REPORT



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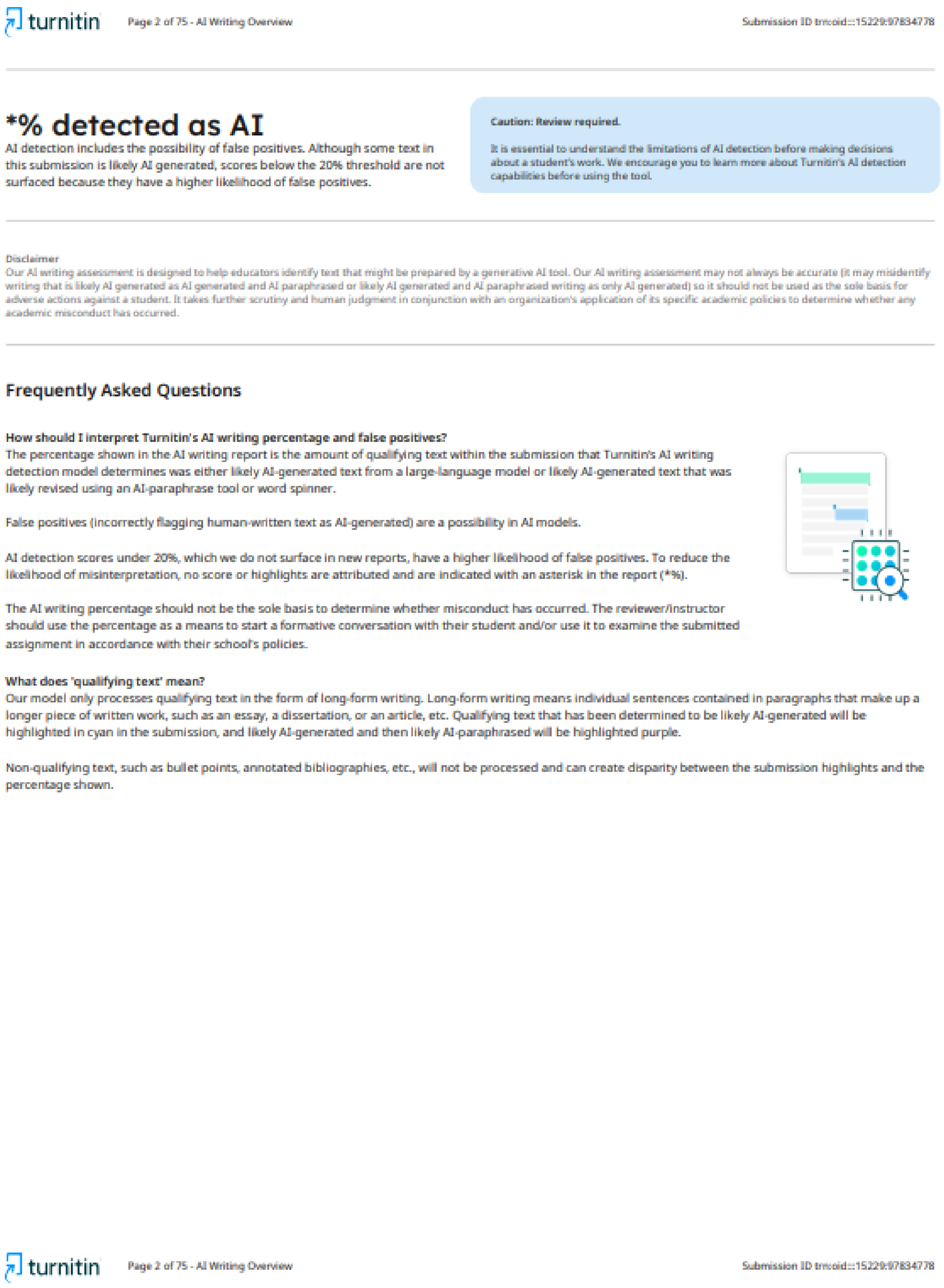

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