# Deep Learning for Early Bacterial Colony Identification through Time-Lapse Imaging

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# Background

### The Need for Faster Bacterial Identification

- ✓ The Urgency of Timely Diagnosis: Rapid and accurate identification of bacterial species is critical for effective treatment and improved patient outcomes. Delays in identification can lead to prolonged illness or the development of antibiotic resistance.
- ✓ Limitations of Traditional Methods:
- ✓ Time-Consuming: Conventional methods, which rely on visible colony growth and biochemical tests, often take several days to a week to yield a result.
- ✓ Labor-Intensive: These processes require skilled technicians for manual observation and a series of lab procedures, which increases human resource costs.
- ✓ Subjective: Colony morphology can be open to subjective interpretation, potentially leading to inconsistent results.

# Microbiological testing



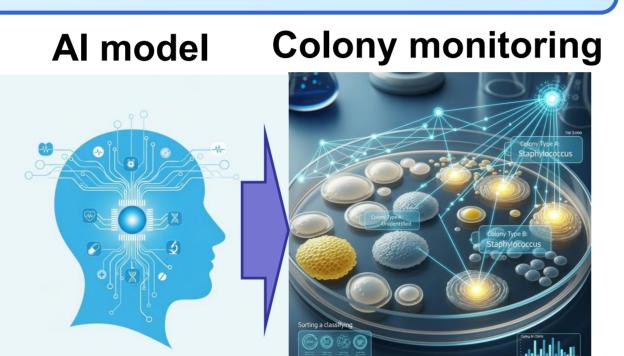
Culture

Identification

Biochemical testing or TOF-MAS testing

## Early Bacterial Colony Identification through Time-Lapse Imaging

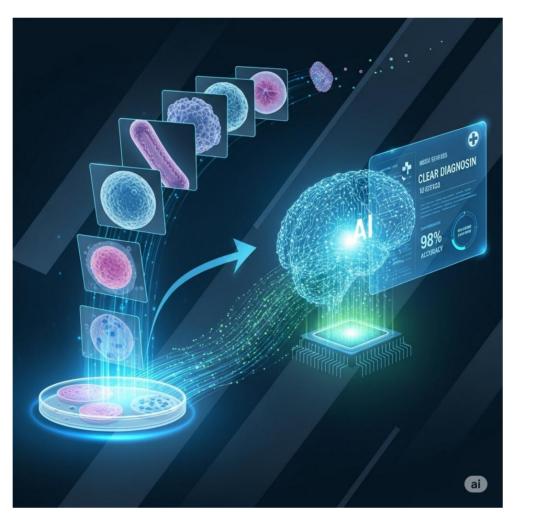
✓ Our Proposed Solution: To overcome these challenges, we propose a novel approach that combines time-lapse imaging with deep learning. This method aims to capture and analyze colony features from the earliest stages of growth, enabling a more rapid and objective identification of bacterial species.



# Objectives

The primary goal of this study is to develop a novel AI model that uses a combination of time-lapse imaging and deep learning to enable rapid and accurate bacterial identification.

- ✓ Achieve Rapid Identification: Analyze colony growth at a much earlier stage than traditional methods to identify bacterial species faster.
- ✓ Improve Objectivity and Accuracy: Ensure objective and highly accurate identification using AI, reducing reliance on subjective human expertise.
- ✓ Increase Efficiency: Automate the culture process to save time and reduce labor in microbiology.
- ✓ Contribute to Early Treatment: Facilitate faster and more appropriate treatment for infectious diseases through rapid diagnosis.



# Results

# 16 hours 24 hours 32 hours 40 hours 48 hours Escherichia coli Klebsiella pneumoniae Serratia marsescens Hafnia alvei Enterobacter cloacae

# Acknowledgement

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# **Conflict of Interest**

The authors have no financial conflicts of interest to disclose concerning the presentation.

## **Materials and Methods**

#### 1. Materials

American Type Culture Collection (ATCC) Strains:

#### 6 Bacterial Species

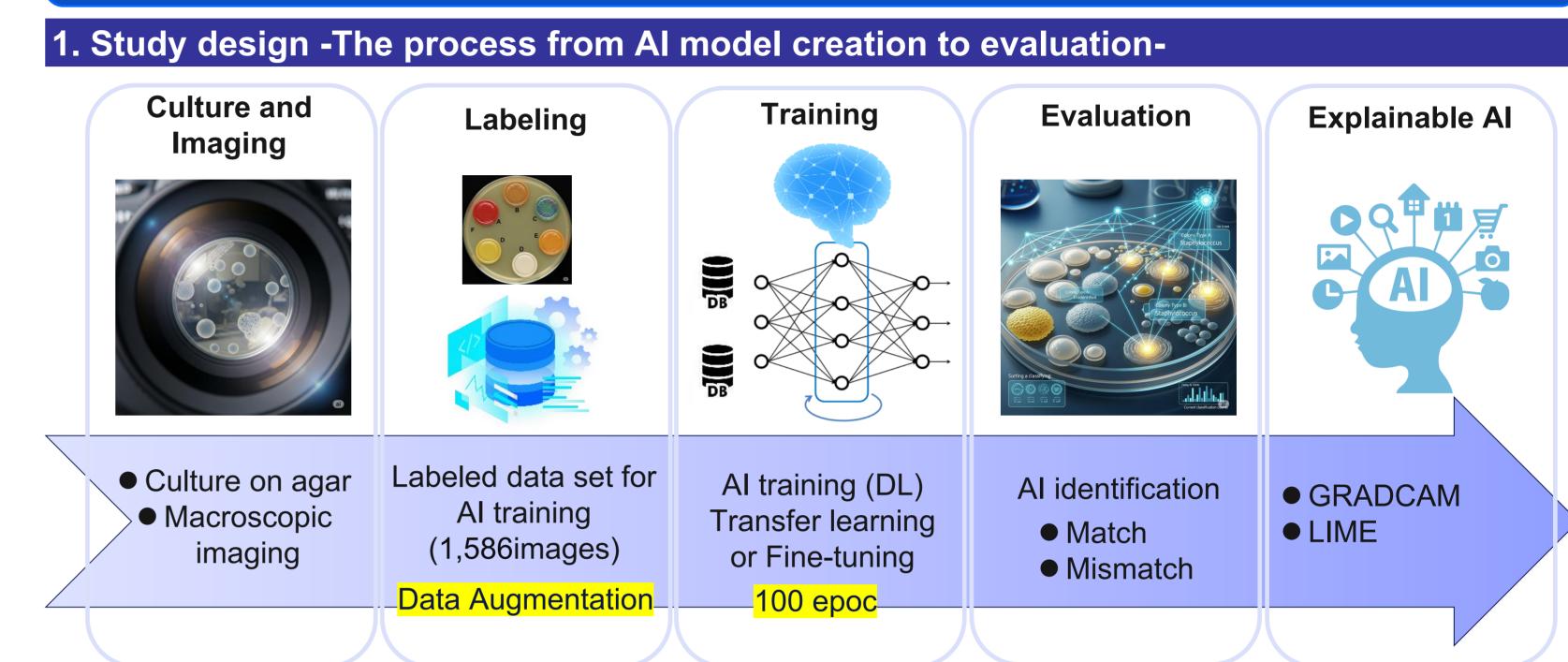
- Escherichia coli: 25922
- Klebsiella pneumoniae: 13883
- Serratia marcescens: 13880
- Hafnia alvei: 51815
- Enterobacter cloacae: 13047
- Proteus mirabilis: 21100

#### 2. Culture and imaging

16, 24, 32, 40, and 48 hours

- ①Culture at 35 °C for 5–6 hours in HI broth until McF reaches 0.5
- ②Spread 20 µL of a 10,000-fold diluted bacterial suspension onto DHL agar plates
- 3 Photograph colonies on plates cultured at 35 °C for
- 4 Photographed using a digital SLR camera (CANON INC. EOS 250D) at 90 degrees angle with a focal length of 260 mm.

# Al modeling with Deep Learning



## 2. Architecture and Configuration

- Anaconda3.0 and Python3.5
- Libraries: Nnabla (SONY.INC)
- CPU: Intel(R) Core(TM) i7-12700 3.6GHz
- GPU: NVIDIA GeForce RTX 4090/24GB
- Architecture: ResNet-18 model

Proteus mirabilis

Total

2. Hold-out validation

## 3. Training and validation data

48

317

- The AI training dataset consisted of 1,586 macroscopic images of bacterial colony.
- The dataset was divided into a training set (80%) and a validation set (20%).

48

317

48

313

**Number of images** Category (Bacterial species) 16 hours 24 hours 32 hours 40 hours 48 hours Escherichia coli 41 40 41 41 41 59 65 59 59 Klebsiella pneumoniae Serratia marsescens 47 47 Hafnia alvei 55 59 59 63 63 Enterobacter cloacae

316

48

323

#### Total accuracy / F1-score 16 hour 24 hour 32 hour 40 hour 0.984 1.000 1.000 **Total accuracy** 1.000 0.938 0.987 1.000 1.000 0.956 **Average F1-score** 0.900 0.968 0.625 1.000 1.000 1.000 0.875 1.000 0.984 0.800 1.000 1.000 1.000 1.000 K.pneumoniae 0.956 0.700 1.000 S.marsescens Recall 0.600 1.000 0.929 1.000 1.000 H.alvei 0.500 1.000 1.000 1.000 1.000 E.cloacae 1.000 1.000 1.000 P.mirabilis 0.400 1.000 1.000 0.300 1.000 1.000 1.000 1.000 1.000 K.pneumoniae 0.200 0.929 0.917 1.000 1.000 S.marsescens 0.100 Precision 0.818 1.000 1.000 1.000 0.000 1.000 1.000 1.000 1.000 1.000 P.mirabilis Recall Precision 1.000 1.000 0.900 0.900 0.800 0.800 0.700 0.700 0.600 0.600 0.500 0.500 0.400 0.400 0.300 0.300 0.200 0.200 0.100 0.100 0.000 0.000

## Summary

- The AI model demonstrates high accuracy in identifying bacterial species from colonies growing on agar media.
- This AI model contributes to early-period bacterial species estimation.

# Conclusion

- •This deep learning-based approach offers a non-invasive, high-throughput solution for automated bacterial identification, potentially reducing turnaround time in clinical microbiology laboratories and improving patient outcomes.
- •Further research will focus on expanding the dataset, validating the model with diverse strains, and integrating it into an automated diagnostic platform.