ABSTRACT

- Archaeology has a major role in a country’s heritage.
- To identify the important sites, we make use of remote sensing techniques [Hyperspectral Imaging], satellite thermography, and the satellite images provide data for mapping of the cultural heritage site areas with some minimal resolution.
- This helps in monitoring cultural heritage in areas affected by conflict or natural disasters, including the use of satellite imagery, is a critical step to start planning for recovery.

INTRODUCTION

- The heritage monuments become relevant to a group as a part of their history or culture due to their artistic, historical, political, technical, or architectural importance.
- Machine Learning and Deep Learning are advancing, spurring progress in image recognition, enabling computer vision to achieve newer heights.
- There is increased coverage of landmarks and monuments of the world, bringing about a need to connect the physical presence of a structure to its digital presence.
- Inadequate environmental conditions, climate change, the massification of tourism, and insufficient management and resources are nowadays the major conservation threats to World Heritage Sites.
- Thus, the automatic identification of the monument comes into play.
- In this work, we are using deep learning techniques for the classification of images of architectural heritage, specifically through the use of convolutional neural networks (CNN)

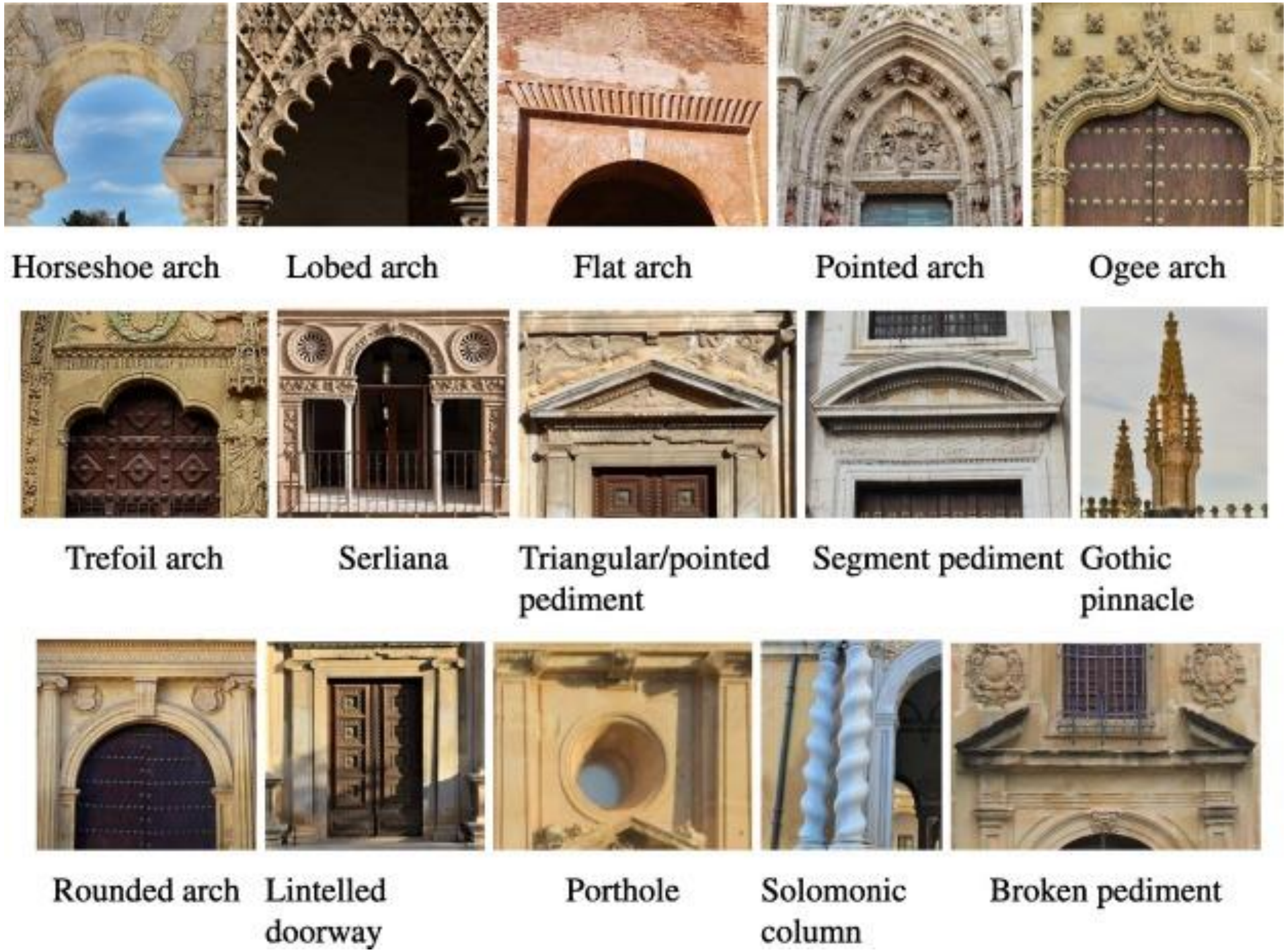
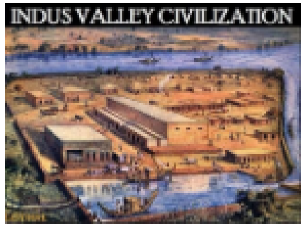


Figure: illustrates the characteristic elements of each style.

Table-1: Top Heritage Sites in India

S.NO.	Heritage Site	Location	Heritage Status
1.	 The Harappan or The Indus- Valley Civilization	Located in the Indus River valley. Its two large cities, Harappa, and Mohenjo-Daro, were in present-day Pakistan's Punjab and Sindh provinces, respectively.	The earliest known culture of the Indian subcontinent of the kind now called "urban" and the largest of the four ancient civilizations, which also included Egypt, Mesopotamia, and China.
2.	 Fatehpur Sikri	Agra, Uttar Pradesh	Built during the reign of Akbar, Fatehpur Sikri is home to several iconic landmarks like Birbal's Palace, Tomb of Salim Chisti and Jama Masjid.
3.	 Undersea Dwaraka	Dwaraka, Gujarat	The dwelling place of lord Krishna has been discovered; The findings add to the belief that all that was written in our scriptures was no mere assumption.

4.	 Ayodhya Dispute	Ayodhya, near river Sarayu, Uttar Pradesh.	One of the most sacred places to visit in India by the Hindu community. It is famed for its historical and mythological stories, beautiful temples, legends surrounding the Hindu epic Ramayana and Vishnu and much more.
5.	 Ellora Caves	Aurangabad, Maharashtra.	The Ellora caves are renowned for their extraordinary architecture. Both the caves have sculptures.
6.	 Ajantha Caves	Aurangabad, Maharasthra.	The Ajanta caves have some of India's most sophisticated ancient paintings.

Fig 1: Satellite image of Harappa

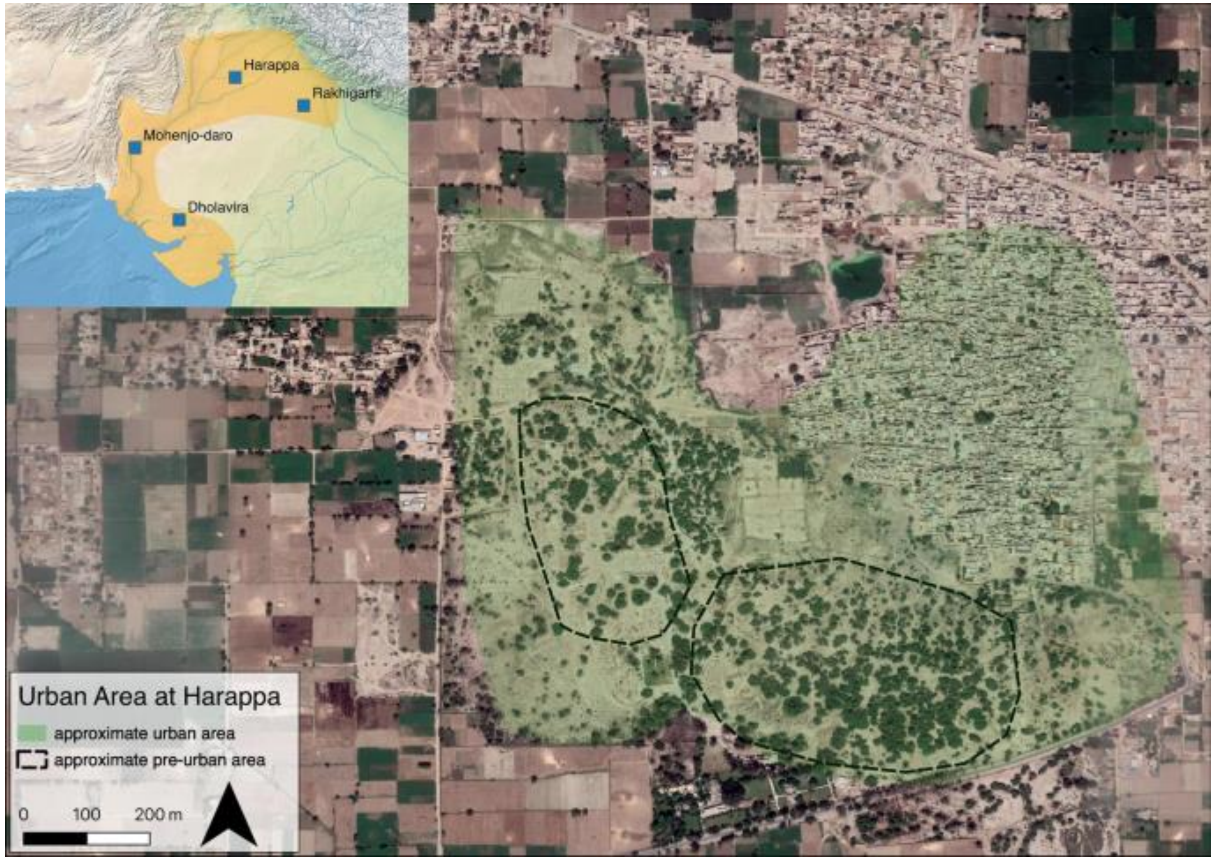
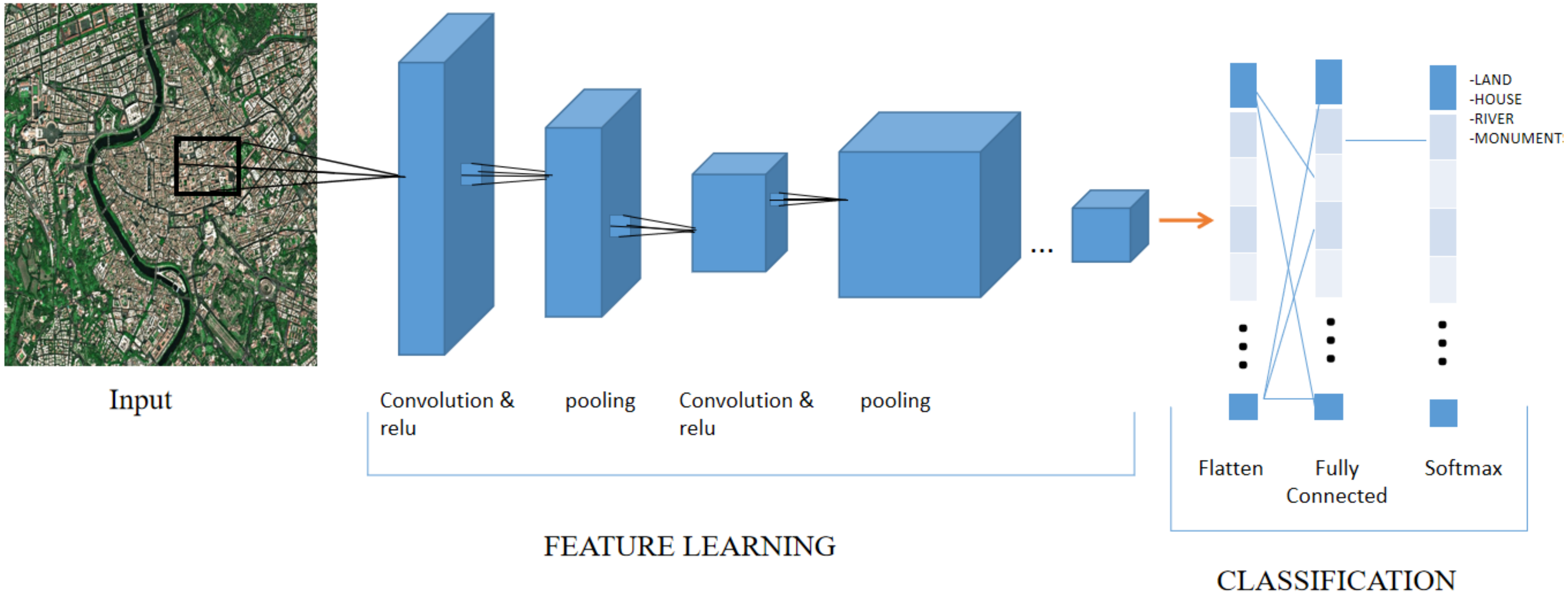


Fig 2: Satellite image of urban area

PROPOSED WORK

- DESIGN/ FRAMEWORK



MODULES

- Input
- Image preprocessing
- Model building
- Model saving
- Model testing
- Image classification

Technologies Used

- RESENET – 50
- Data Augmentation
- VGG – 16
- Alex Net [Convolutional Neural Networks]
- Inception - V3 Model
- Mobile Net
- Open CV

OUTPUT

```
data = pd.DataFrame(df['landmark_id'].value_counts())
#index the data frame
data.reset_index(inplace=True)
data.columns=['landmark_id','count']

print(data.head(10))
print(data.tail(10))
```

```
   landmark_id  count
0         1924    944
1           27    504
2          454    254
3         1346    244
4         1127    201
5          870    193
6         2185    177
7         1101    162
8          389    140
9          219    139
      landmark_id  count
1010         1404      2
1011         1403      2
1012          585      2
1013          604      2
1014          611      2
1015          625      2
1016         1250      2
1017         2239      2
1018          655      2
1019         1064      2
```

Fig.1: Detection of Landmark

```
print(data['count'].describe())#statistical data for the distribution
plt.hist(data['count'],100,range = (0,944),label = 'test')#Histogram of the distribution
plt.xlabel("Amount of images")
plt.ylabel("Occurences")
```

```
count    1020.000000
mean       19.608824
std        41.653684
min         2.000000
25%         5.000000
50%         9.000000
75%        21.000000
max       944.000000
Name: count, dtype: float64
```

```
Text(0, 0.5, 'Occurences')
```

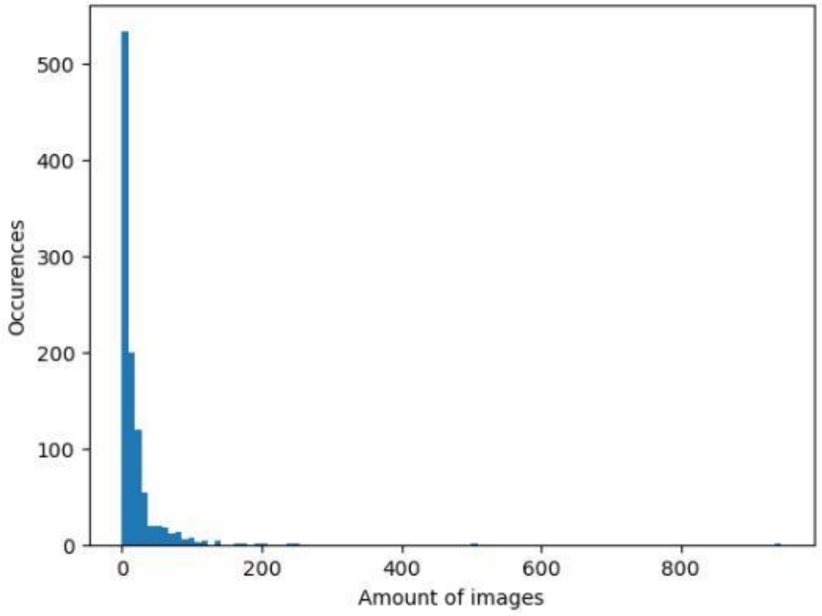


Fig – 2: Statistical Data Evaluation
Histogram of the distribution

```
print("Amount of classes with five and less datapoints:", (data['count'].between(0,5)).sum())

print("Amount of classes with with between five and 10 datapoints:", (data['count'].between(5,10)).sum())

n = plt.hist(df["landmark_id"],bins=df["landmark_id"].unique())
freq_info = n[0]

plt.xlim(0,data['landmark_id'].max())
plt.ylim(0,data['count'].max())
plt.xlabel('Landmark ID')
plt.ylabel('Number of images')
```

```
Amount of classes with five and less datapoints: 322
Amount of classes with with between five and 10 datapoints: 342

Text(0, 0.5, 'Number of images')
```

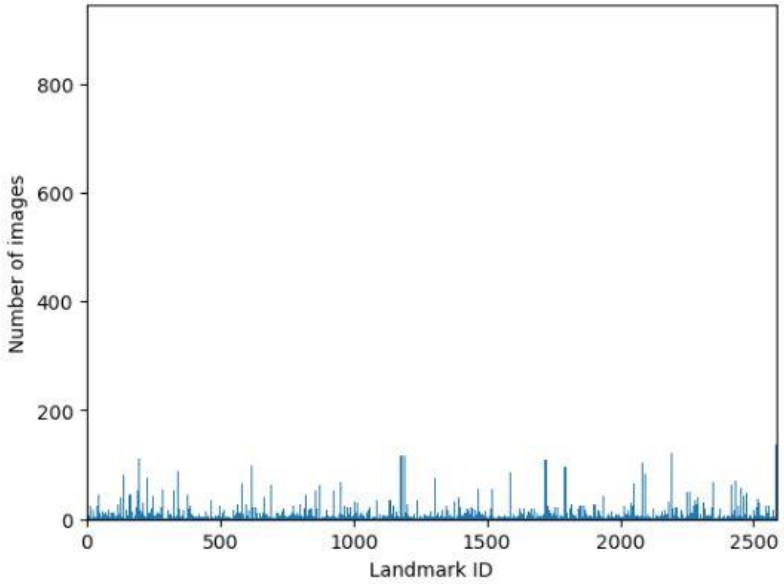


Fig – 3: Statistical classification of images using landmarks

```python
print("4 sample images from random classes:")
fig=plt.figure(figsize=(16, 16))
for i in range(0,4):
    base_path="C:\\Users\\Image"
    a = random.choices(os.listdir(base_path), k=4)
    #a = random.choices(os.listdir(base_path))
    folder = base_path+'\\'+a[i] #+'\\'+a[1]+'\\'+a[2]
    random_img = random.choice(os.listdir(folder))
    img = np.array(Image.open(folder+'\\'+random_img))
    fig.add_subplot(1, 4, i+1)
    plt.imshow(img)
    plt.axis('off')

plt.show()
```

```
4 sample images from random classes:
```

Fig – 4: Sample images from random classes
[Data Pooling]

Model: "sequential_1"

Layer (type)	Output Shape	Param #
batch_normalization_1 (BatchNormalization)	(None, 224, 224, 3)	12
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv4 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv4 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv4 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
fc1 (Dense)	(None, 4096)	102764544
fc2 (Dense)	(None, 4096)	16781312
dense_1 (Dense)	(None, 1020)	4178940

Total params: 143,749,192
Trainable params: 143,749,186
Non-trainable params: 6

Fig – 5: Image data segments' segregation

RESULTS

- Used ResNet50 as pre-trained model in transfer learning
- Achieved training loss of 11% over 30 epochs.
- Achieved classification accuracy of 91% over 30 epochs.
- Achieved precision and recall of 88% and 82% respectively.

An illustrative example of Tensor board is presented in figure

LITERATURE SURVEY

- According to, Journal of Cultural Heritage Volume 51, September–October 2021, Pages 37-49. The deep learning method applied to the detection and mapping of stone deterioration in open-air sanctuaries of the Hittite period in Anatolia.
- According to, Journal of Indian Monument Detection using Deep Learning Various type of Deep Learning architectures have been used to recognize monuments and achieve a good performance, so, five best performing architectures namely InceptionV3, MobileNet, RestNet50, VGG16 and Alex Net was applied to recognize monument in this study.

CONCLUSION & FUTURE WORK

- We hope that our attempt to understand and document the optimal method for capturing and processing multispectral images of heritage artifacts using a CNN with narrowband light sources will help others to consider their method, produce the best quality results in their approach, and document and share results and data in a way which will benefit the wider cultural heritage imaging community.
- Using satellite thermography and imagery the future work can be considered.
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THANK YOU