Predicting Resale Value of Knives from a Texas Government Surplus Store

Using Machine Learning to Support an Ebay Store's Financial Success

Data Exploration and Modeling

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Model

In [1]:
```
from sklearn.model_selection import train_test_split
import os
from collections import Counter

import pandas as pd
import  json
import requests
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import ast
import re

from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.layers import Dense, Input, GlobalMaxPooling1D
from tensorflow.keras.layers import LSTM, Embedding, Flatten, GRU
from tensorflow.keras.layers import Conv1D, MaxPooling1D, GlobalMaxPooling2D
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dropout, BatchNormalization
from tensorflow.keras.layers import SimpleRNN
from tensorflow.keras.models import Model
from keras import models
from keras import layers
import tensorflow as tf
from keras.utils import plot_model
from sklearn.metrics import mean_absolute_error
from keras_preprocessing.image import ImageDataGenerator
```

In [2]:
```
plt.style.use('dark_background')
```

Function Definition

In [3]:

```
def apply_iqr_filter(df):

    price_Q1 = df['converted_price'].quantile(0.25)
    price_Q3 = df['converted_price'].quantile(0.75)
    price_iqr = price_Q3 - price_Q1

    profit_Q1 = df['profit'].quantile(0.25)
    profit_Q3 = df['profit'].quantile(0.75)
    profit_iqr = profit_Q3 - profit_Q1

    ROI_Q1 = df['ROI'].quantile(0.25)
    ROI_Q3 = df['ROI'].quantile(0.75)
    ROI_iqr = ROI_Q3 - ROI_Q1

    price_upper_limit = price_Q3 + (1.5 * price_iqr)
    price_lower_limit = price_Q1 - (1.5 * price_iqr)

    profit_upper_limit = profit_Q3 + (1.5 * profit_iqr)
    profit_lower_limit = profit_Q1 - (1.5 * profit_iqr)

    ROI_upper_limit = ROI_Q3 + (1.5 * ROI_iqr)
    ROI_lower_limit = ROI_Q1 - (1.5 * ROI_iqr)

#     print(f'Brand: {df.brand[0]}')
#     print(f'price upper limit: ${np.round(price_upper_limit,2)}')
#     print(f'price lower limit: ${np.round(price_lower_limit,2)}')
#     print('-----------------------------------')
#     print(f'profit upper limit: ${np.round(profit_upper_limit,2)}')
#     print(f'profit lower limit: ${np.round(profit_lower_limit,2)}')
#     print('-----------------------------------')
#     print(f'ROI upper limit: {np.round(ROI_upper_limit,2)}%')
#     print(f'ROI lower limit: {np.round(ROI_lower_limit,2)}%')
#     print('-----------------------------------')


    new_df = df[(df['converted_price'] < price_upper_limit) &
                (df['converted_price'] > price_lower_limit) &
                (df['profit'] < profit_upper_limit) &
                (df['ROI'] > profit_lower_limit) &
                (df['profit'] < ROI_upper_limit) &
                (df['ROI'] > ROI_lower_limit)]

    return new_df
#download jpg urls from dataFrame
def download(row):
    filename = os.path.join(root_folder, str(row.name) + im_extension)

# create folder if it doesn't exist
    os.makedirs(os.path.dirname(filename), exist_ok=True)

    url = row.Image
#     print(f"Downloading {url} to {filename}")

    try:
        r = requests.get(url, allow_redirects=True)
        with open(filename, 'wb') as f:
            f.write(r.content)
    except:
        print(f'{filename} error')


def cardinality_threshold(column,threshold=0.75,return_categories_list=True):
    #calculate the threshold value using
    #the frequency of instances in column
    threshold_value=int(threshold*len(column))
    #initialize a new list for lower cardinality column
    categories_list=[]
    #initialize a variable to calculate sum of frequencies
    s=0
    #Create a dictionary (unique_category: frequency)
    counts=Counter(column)

    #Iterate through category names and corresponding frequencies after sorting the categories
    #by descending order of frequency
    for i,j in counts.most_common():
        #Add the frequency to the total sum
        s += dict(counts)[i]
        #append the category name to the categories list
        categories_list.append(i)
        #Check if the global sum has reached the threshold value, if so break the loop
        if s >= threshold_value:
            break
      #append the new 'Other' category to list
    categories_list.append('Other')

    #Take all instances not in categories below threshold
```

```
    #that were kept and lump them into the
    #new 'Other' category.
    new_column = column.apply(lambda x: x if x in categories_list else 'Other')

    #Return the transformed column and
    #unique categories if return_categories = True
    if(return_categories_list):
        return new_column,categories_list
    #Return only the transformed column if return_categories=False
    else:
        return new_column

def fix(col):
    dd = dict()
    for d in col:
        values = list(d.values())
        if len(values) == 2:
            dd[values[0]] = values[1]
    return dd

#function for extracted item Specifics from Shopping API data
def transform_item_specifics(df, perc=90.0):

    df.dropna(subset=['ItemSpecifics'], inplace=True)
    df['ItemSpecifics'] = df['ItemSpecifics'].apply(lambda x: ast.literal_eval(x))
    df['item_list'] = df['ItemSpecifics'].apply(lambda x: x['NameValueList'])

    df['ItemSpecifics'] = df['ItemSpecifics'].apply(lambda x: [x['NameValueList']] if isinstance(x['NameValueList'

    df['ItemSpecifics'] = df['ItemSpecifics'].apply(fix)

    df = pd.json_normalize(df['ItemSpecifics'])

    min_count =  int(((100-perc)/100)*df.shape[0] + 1)
    mod_df = df.dropna(axis=1,
                       thresh=min_count)

    return mod_df

# This function removes noisy data
#lots/sets/groups of knives can
#confuse the model from predicting
#the appropriate value of individual knives
def data_cleaner(df):
    lot = re.compile('(?<!-\S)lot(?![^\s.,:?!])')
    group = re.compile('(group)')
    is_set = re.compile('(?<!-\S)set(?![^\s.,?!])')
    df['title'] = df['title'].str.lower()
    trim_list = [lot,group,is_set]
    for item in trim_list:
        df.loc[df['title'].apply(lambda x: re.search(item, x)).notnull(), 'trim'] = 1
    to_drop = df.loc[df['trim'] == 1].index
    df.drop(to_drop, inplace=True)
    df.drop('trim', axis=1, inplace=True)

    return df



def prepare_listed(listed_data_df, Ids_df):
    listed_data_df.drop('galleryPlusPictureURL', axis=1, inplace=True)

    Ids_df.rename({'Title': 'title',
                   'ItemID': 'itemId'},
                    axis=1,inplace=True)

    Ids_df.drop(['ConditionID','ConvertedCurrentPrice'],
                         axis=1, inplace=True)
    Ids_df['title'] = Ids_df['title'].str.lower()

    df_merged = listed_data_df.merge(Ids_df)

    df_spec = transform_item_specifics(df_merged, perc=65.0)

    df_spec.drop('Brand', axis=1, inplace=True)

    tot_listed_df = df_merged.join(df_spec)

    listed_knives = data_cleaner(tot_listed_df).copy()
    listed_knives.drop(['sellingStatus', 'shippingInfo',
                        'GalleryURL', 'ItemSpecifics',
                        'item_list', 'listingInfo'],
                        axis=1, inplace=True)
    listed_used_knives = listed_knives.loc[listed_knives['condition'] != 1000.0]
    listed_used_knives.reset_index(drop=True, inplace=True)

```

```
    return listed_used_knives


def prepare_tera_df(df, x, overhead_cost=3):
    df['price_in_US'] = df['price_in_US'].str.replace("$", "")
    df['price_in_US'] = df['price_in_US'].str.replace(",", "")
    df['price_in_US'] = df['price_in_US'].apply(float)

    df['shipping_cost'] = df['shipping_cost'].str.replace("$", "")
    df['shipping_cost'] = df['shipping_cost'].str.replace(",", "")
    df['shipping_cost'] = df['shipping_cost'].apply(float)

    df['brand'] = list(bucket_dict.keys())[x]
    df['converted_price'] = (df['price_in_US'] + df['shipping_cost'])
    df['cost'] = list(bucket_dict.values())[x] + overhead_cost + 4.95
    df['profit'] = ((df['converted_price']*.87) -  df['cost'])
    df['ROI'] = (df['profit']/ df['cost'])*100.0

    return df

```

Load Data

In [4]:

```
#load Finding API data
df_bench = pd.read_csv("listed_data/df_bench.csv")
df_buck = pd.read_csv("listed_data/df_buck.csv")
df_case = pd.read_csv("listed_data/df_case.csv")
df_caseXX = pd.read_csv("listed_data/df_CaseXX.csv")
df_crkt = pd.read_csv("listed_data/df_crkt.csv")
df_kersh = pd.read_csv("listed_data/df_kershaw.csv")
df_sog = pd.read_csv("listed_data/df_sog.csv")
df_spyd = pd.read_csv("listed_data/df_spyderco.csv")
df_vict = pd.read_csv("listed_data/df_victorinox.csv")

#load Shopping API data
bench = pd.read_csv("listed_data/benchIds.csv")
buck = pd.read_csv("listed_data/buckIds.csv")
case = pd.read_csv("listed_data/caseIds.csv")
caseXX = pd.read_csv("listed_data/caseXXIds.csv")
crkt = pd.read_csv("listed_data/crktIds.csv")
kershaw = pd.read_csv("listed_data/kershawIds.csv")
sog = pd.read_csv("listed_data/sogIds.csv")
spyd = pd.read_csv("listed_data/spydIds.csv")
vict = pd.read_csv("listed_data/victIds.csv")

#Load scraped terapeak sold data
sold_bench = pd.read_csv("terapeak_data/bench_scraped2.csv")
sold_buck1 = pd.read_csv("terapeak_data/buck_scraped2.csv")
sold_buck2 = pd.read_csv("terapeak_data/buck_scraped2_reversed.csv")
sold_case = pd.read_csv("terapeak_data/case_scraped2.csv")
sold_caseXX1 = pd.read_csv("terapeak_data/caseXX_scraped2.csv")
sold_caseXX2 = pd.read_csv("terapeak_data/caseXX2_reversed.csv")
sold_crkt = pd.read_csv("terapeak_data/crkt_scraped.csv")
sold_kershaw1 = pd.read_csv("terapeak_data/kershaw_scraped2.csv")
sold_kershaw2 = pd.read_csv("terapeak_data/kershaw_scraped2_reversed.csv")
sold_sog = pd.read_csv("terapeak_data/SOG_scraped2.csv")
sold_spyd = pd.read_csv("terapeak_data/spyd_scraped2.csv")
sold_vict1 = pd.read_csv("terapeak_data/vict_scraped.csv")
sold_vict2 = pd.read_csv("terapeak_data/vict_reversed.csv")

sold_list = [sold_bench,sold_buck1,
             sold_buck2,sold_case,
             sold_caseXX1,sold_caseXX2,
             sold_crkt,sold_kershaw1,
             sold_kershaw2,sold_sog,
             sold_spyd, sold_vict1,
             sold_vict2]


listed_df = pd.concat([df_bench,df_buck,
                       df_case,df_caseXX,
                       df_crkt,df_kersh,
                       df_sog,df_spyd,
                       df_vict])

used_listed_df = listed_df.loc[listed_df['condition'] != 1000.0].copy()

cols = ['title','pictureURLLarge','converted_price','brand','profit','ROI']
used_listed = used_listed_df[cols].copy()
used_listed.dropna(subset=['pictureURLLarge'], inplace=True)

used_listed.reset_index(drop=True, inplace=True)


bucket_dict = {'benchmade': 45.0,
               'buck': 20.0,
               'case': 20.0,
               'crkt': 15.0,
               'kershaw': 15.0,
               'sog': 15.0,
               'spyderco': 30.0,
               'victorinox': 20.0
               }
```

Prepare Data

In [5]:
```
for dataframe in sold_list:
    dataframe.rename({'Text': 'title',
                      'shipping_': 'shipping_cost'},
                     axis=1, inplace=True)

    dataframe['date_sold'] = pd.to_datetime(dataframe['date_sold'])

sold_buck = pd.concat([sold_buck1,sold_buck2])
sold_caseXX = pd.concat([sold_caseXX1,sold_caseXX2])
sold_kershaw = pd.concat([sold_kershaw1,sold_kershaw2])
sold_vict = pd.concat([sold_vict1,sold_vict2])

sold_bench = prepare_tera_df(sold_bench, 0)
sold_buck = prepare_tera_df(sold_buck, 1)
sold_case = prepare_tera_df(sold_case, 2)
sold_caseXX = prepare_tera_df(sold_caseXX, 2)
sold_crkt = prepare_tera_df(sold_crkt, 3)
sold_kershaw = prepare_tera_df(sold_kershaw, 4)
sold_sog = prepare_tera_df(sold_sog, 5)
sold_spyd = prepare_tera_df(sold_spyd, 6)
sold_vict = prepare_tera_df(sold_vict, 7)
```

In [6]:
```
for dataframe in sold_list:
    dataframe['title'] = dataframe['title'].str.lower()
    dataframe['title'] = dataframe['title'].str.strip()
    dataframe.drop_duplicates(
        subset = ['date_sold','price_in_US',
                  'shipping_cost'],
        keep = 'last', inplace=True)
```

In [7]:
```
sold_df = pd.concat([sold_bench, sold_buck,
                     sold_case, sold_caseXX,
                     sold_crkt, sold_kershaw,
                     sold_sog, sold_spyd,
                     sold_vict])

sold_knives = data_cleaner(sold_df).copy()


df = pd.concat([sold_knives,used_listed]).copy()
df['Image'].fillna(df['pictureURLLarge'], inplace=True)

df = apply_iqr_filter(df).copy()
df.reset_index(drop=True, inplace=True)
```

In [8]:
```
def clean_text(x):
    pattern = r'[^a-zA-z0-9\s]'
    text = re.sub(pattern, '', x)
    return text
```

In [9]:
```
df['title'] = df['title'].apply(clean_text)
```

In [10]:
```
df['title'].sample(20).apply(print)
```

```
case xx pocket knife  folding 2bladecase xx pocket knife  folding 2blade
victorinox swiss army knife classic sd  pink camo 58mm multitool nice
case xx 6318 ss red delrin stockman pocket knife used case xx 6318 ss red delrin stockman pocket knife used
crkt nirk tighe 2 folding knife 5240 excellentcrkt nirk tighe 2 folding knife 5240 excellent
case xx copperhead knife 6249 bone handles unused 1979case xx copperhead knife 6249 bone handles unused 1979
crkt crawford falcon 6242 folding pocket knifecrkt crawford falcon 6242 folding pocket knife
case xx baby swamp rat knife 19401964 era reddish bone handles 1 2 carry nr case xx baby swamp rat knife 19401964 era reddish bone handles 1 2 carry nr
kershaw ao cryo 1555ti folding pocket knifekershaw ao cryo 1555ti folding pocket knife
benchmade 710 mchenry  williams d2 folding pocket knifebenchmade 710 mchenry  williams d2 folding pocket knife
2015 case xx saw cut amber bone medium stockman knife 6318cv chrome vanadium 2015 case xx saw cut amber bone medium stockman knife 6318cv chrome vanadium
case xx stockman  pocket worn 25th anniversary knife 6347 sscase xx stockman  pocket worn 25th anniversary knife 6347 ss
victorinox alox electrician  swiss army knife 93 mmvictorinox alox electrician  swiss army knife 93 mm
victorinox evolution grip s18 swiss army knife 73victorinox evolution grip s18 swiss army knife 73
2019 case xx trapper knife keep your hands sharp tour lasered bone serial  0032019 case xx trapper knife keep your hands sharp tour lasered bone serial  003
original 1994 buck crosslock 180 knife serrated blade usa madeoriginal 1994 buck crosslock 180 knife serrated blade usa made
buck usa bantam mossy oak camo 284 folding pocket knife
kershaw steven seagal knife 1680 japan aus8a ken onion designkershaw steven seagal knife 1680 japan aus8a ken onion design
vintage buck 110 381 1980s hunter knife w box  sheath  paperwork very nicevintage buck 110 381 1980s hunter knife w box  sheath  paperwork very nice
kershaw 1660ol leek pocket knife  olive green assisted opening liner lock usakershaw 1660ol leek pocket knife  olive green assisted opening liner lock usa
new kershaw 1555ti cryo hinderer designed assisted opening knife lnnew kershaw 1555ti cryo hinderer designed assisted opening knife ln
```

Out[10]:
```
28429    None
75017    None
27880    None
35157    None
23059    None
33358    None
21677    None
43359    None
3243     None
29370    None
22637    None
61215    None
65114    None
29457    None
9123     None
67824    None
47152    None
4874     None
42321    None
38806    None
Name: title, dtype: object
```

In [11]:
```
df['title_len'] = df['title'].apply(lambda x: len(x))
df['word_count'] = df['title'].apply(lambda x: len(x.split()))
```

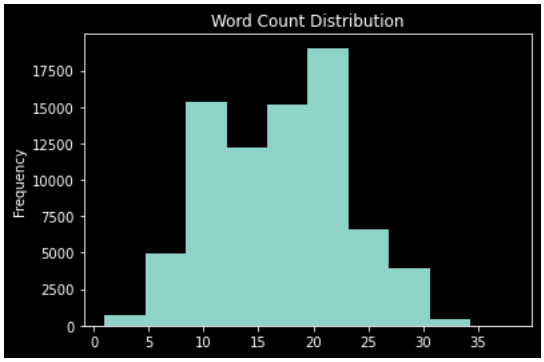
In [12]:
```
def avg_word_len(x):
    words = x.split()
    word_len = 0
    for word in words:
        word_len += len(word)

    return word_len / len(words)
```

In [13]:
```
df['avg_word_len'] = df['title'].apply(lambda x: avg_word_len(x))
```

In [14]:
```
# pd.options.plotting.backend = "plotly"
```

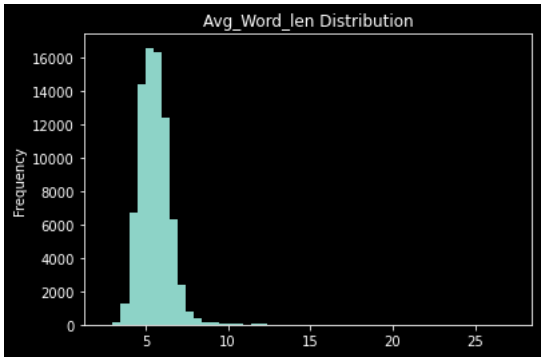
In [15]:
```
df['word_count'].plot(kind = 'hist', title = 'Word Count Distribution')
```

Out[15]: <AxesSubplot:title={'center':'Word Count Distribution'}, ylabel='Frequency'>

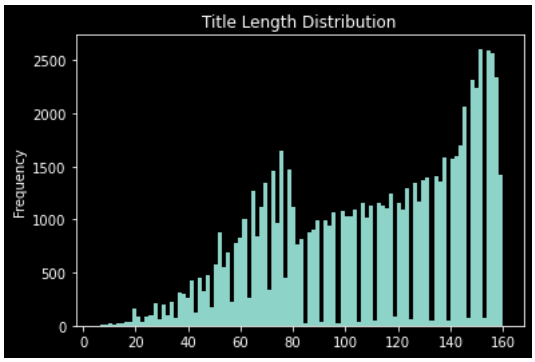


In [16]:
```
df['avg_word_len'].plot(kind='hist', bins = 50, title = 'Avg_Word_len Distribution')
```

Out[16]: <AxesSubplot:title={'center':'Avg_Word_len Distribution'}, ylabel='Frequency'>



In [17]:
```
df['title_len'].plot(kind='hist', bins= 100,title = 'Title Length Distribution');
```



In [18]:
```
df.describe()
```

Out[18]:

	price_in_US	shipping_cost	converted_price	cost	profit	ROI	title_len	word_count	avg_word_len
count	66768.000000	66768.000000	78330.000000	66768.000000	78330.000000	78330.000000	78330.000000	78330.000000	78330.000000
mean	45.969092	4.315289	50.044127	28.754727	15.728080	54.837503	109.446062	17.086340	5.534031
std	35.153294	3.598604	36.026730	7.272042	28.695811	103.741175	36.561769	6.116623	0.982619
min	0.010000	0.000000	6.940000	22.950000	-38.812500	-73.853309	5.000000	1.000000	2.500000
25%	19.990000	0.000000	22.182500	22.950000	-5.600000	-22.325490	78.000000	12.000000	4.888889
50%	35.000000	4.950000	38.740000	27.950000	7.065000	26.064401	114.000000	17.000000	5.466667
75%	62.000000	5.900000	67.490000	27.950000	29.204950	102.866646	144.000000	22.000000	6.000000
max	167.000000	80.000000	167.490000	52.950000	109.153000	605.666667	160.000000	38.000000	27.200000

Neural network with "title" column as input

In [19]:
```
df_title = df.loc[:, ['title', 'converted_price']]


df_title.rename({'title': 'data',
                 'converted_price': 'labels'},
                axis=1, inplace=True)
```

In [20]:
```
df_title.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 78330 entries, 0 to 78329
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   data    78330 non-null  object
 1   labels  78330 non-null  float64
dtypes: float64(1), object(1)
memory usage: 1.2+ MB
```

In [21]:
```
# df_title['labels'] = (df_title['labels']/mean_price)
Y = df_title['labels'].values
```

In [22]:
```
df_title['data'].sample(10).apply(print)
```

```
2000 case xx usa small stockman pocket knife 6327 ss blue jig bone made in usa2000 case xx usa small stockman pocket knife 6327 ss blue jig bone made in usa
kershaw 1670rd blur pocket knife speedsafe liner lock usa kershaw 1670rd blur pocket knife speedsafe liner lock usa
kershaw folding pocket knife kai 2415kershaw folding pocket knife kai 2415
victorinox signature lite with 1gb memory card swiss army knife  54victorinox signature lite with 1gb memory card swiss army knife  54
spyderco clipitool standard folding knife c208gp plain edge blade black g10spyderco clipitool standard folding knife c208gp plain edge blade black g10
ntsa vntg195286 swiss army victorinox  champion plus  mfunction pkt knifentsa vntg195286 swiss army victorinox  champion plus  mfunction pkt knife
9 empty benchmade knife boxes9 empty benchmade knife boxes
kershaw 1670olblk ken onion design folding pocket knife assisted openkershaw 1670olblk ken onion design folding pocket knife assisted open
case xx mini copperlock smooth abalone pocket knife usa 12020case xx mini copperlock smooth abalone pocket knife usa 12020
used buck 284 pocket knifeused buck 284 pocket knife
```

Out[22]:
```
27488    None
49043    None
38988    None
60169    None
54246    None
58302    None
2386     None
38622    None
24044    None
15348    None
Name: data, dtype: object
```

In [23]:
```
df_train, df_test, Ytrain, Ytest = train_test_split(df_title['data'],
                                                    Y,
                                                    test_size=0.3,
                                                    random_state=51)
```

In [24]:
```
X_val, X_test, Y_val, Y_test = train_test_split(df_test,
                                                Ytest,
                                                test_size=0.5,
                                                random_state=51)
```

GRU

In [25]:
```
#Vectorize vocab
voc_size = 25000
max_len = 30
embedding_features = 35
tokenizer = Tokenizer(num_words=voc_size, oov_token = '<OOV>')
tokenizer.fit_on_texts(df_train)
sequences_train = tokenizer.texts_to_sequences(df_train)
sequences_val = tokenizer.texts_to_sequences(X_val)
sequences_test = tokenizer.texts_to_sequences(X_test)
```

In [26]:
```
#add padding to ensure all inputs are the same size
data_train = pad_sequences(sequences_train, maxlen=max_len, padding= 'post', truncating = 'post')
data_val = pad_sequences(sequences_val, maxlen=max_len, padding= 'post', truncating = 'post')
data_test = pad_sequences(sequences_test, maxlen=max_len, padding= 'post', truncating = 'post')
```

In [27]:
```
data_train.shape
```

Out[27]:
```
(54831, 30)
```

In [28]:
```
model = models.Sequential()
model.add(Embedding(voc_size, embedding_features, input_length = max_len))
model.add(GRU(100))
model.add(Dense(64, activation = 'relu'))
# model.add(Dropout(0.3))
model.add(Dense(32, activation = 'relu'))
model.add(Dropout(0.3))
model.add(Dense(1, activation = 'relu'))
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 30, 35)            875000
_________________________________________________________________
gru (GRU)                    (None, 100)               41100
_________________________________________________________________
dense (Dense)                (None, 64)                6464
_________________________________________________________________
dense_1 (Dense)              (None, 32)                2080
_________________________________________________________________
dropout (Dropout)            (None, 32)                0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 33
=================================================================
Total params: 924,677
Trainable params: 924,677
Non-trainable params: 0
_________________________________________________________________
```

In [29]:
```
# Compile and fit
model.compile(
  loss='MSE',
  optimizer='adam',
  metrics=['mae']
)


print('Training model...')
r = model.fit(
  data_train,
  Ytrain,
  epochs=10,
  validation_data=(data_val, Y_val)
)
```

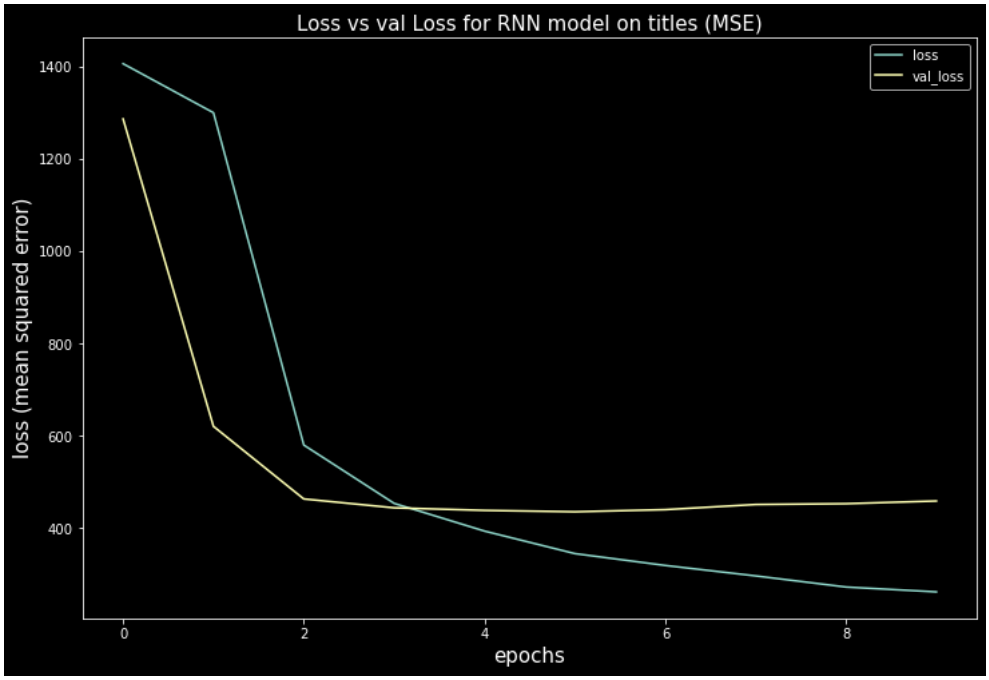
```
Training model...
Epoch 1/10
1714/1714 [==============================] - 28s 16ms/step - loss: 1406.4950 - mae: 29.1902 - val_loss: 1286.9244 - v
al_mae: 28.9204
Epoch 2/10
1714/1714 [==============================] - 27s 16ms/step - loss: 1300.3254 - mae: 27.8673 - val_loss: 620.8804 - va
l_mae: 17.8693
Epoch 3/10
1714/1714 [==============================] - 28s 16ms/step - loss: 580.3170 - mae: 16.7247 - val_loss: 463.5613 - val
_mae: 14.9725
Epoch 4/10
1714/1714 [==============================] - 29s 17ms/step - loss: 453.9511 - mae: 14.5761 - val_loss: 444.3378 - val
_mae: 14.1846
Epoch 5/10
1714/1714 [==============================] - 29s 17ms/step - loss: 393.9201 - mae: 13.4119 - val_loss: 438.7681 - val
_mae: 14.0230
Epoch 6/10
1714/1714 [==============================] - 27s 16ms/step - loss: 345.1503 - mae: 12.5439 - val_loss: 435.7736 - val
_mae: 13.8277
Epoch 7/10
1714/1714 [==============================] - 27s 16ms/step - loss: 319.4977 - mae: 12.0130 - val_loss: 440.4136 - val
_mae: 13.9308
Epoch 8/10
1714/1714 [==============================] - 27s 16ms/step - loss: 296.8629 - mae: 11.5484 - val_loss: 451.5638 - val
_mae: 14.0264
Epoch 9/10
1714/1714 [==============================] - 27s 16ms/step - loss: 272.7390 - mae: 11.0679 - val_loss: 453.2909 - val
_mae: 13.9109
Epoch 10/10
1714/1714 [==============================] - 28s 16ms/step - loss: 262.2486 - mae: 10.8240 - val_loss: 459.1286 - val
_mae: 14.0011
```

In [30]:
```
pred=model.predict(data_test)
```

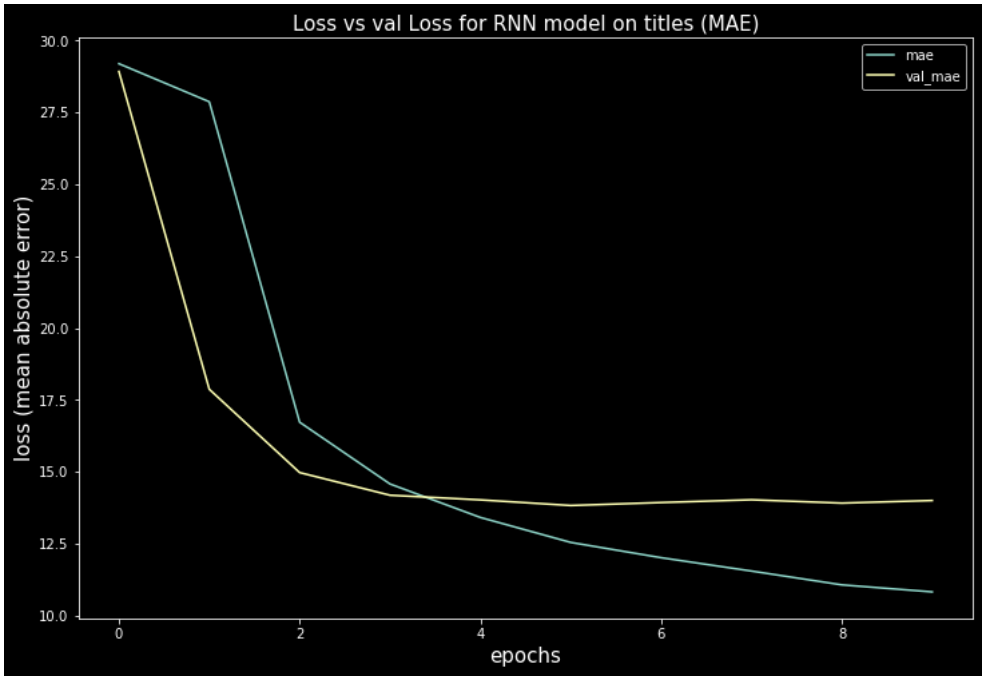
In [31]:
```
test_results = model.evaluate(data_test, Y_test)
```

```
368/368 [==============================] - 1s 3ms/step - loss: 465.1646 - mae: 13.9465
```

In [32]:
```
fig = plt.subplots(figsize=(12,8))
plt.plot(r.history['loss'], label='loss')
plt.plot(r.history['val_loss'], label='val_loss')
plt.title("Loss vs val Loss for RNN model on titles (MSE)", fontsize=15)
plt.xlabel("epochs", fontsize=15)
plt.ylabel("loss (mean squared error)", fontsize=15)
plt.legend();
plt.savefig('images/RNN_GRU_MSE1.png')
```

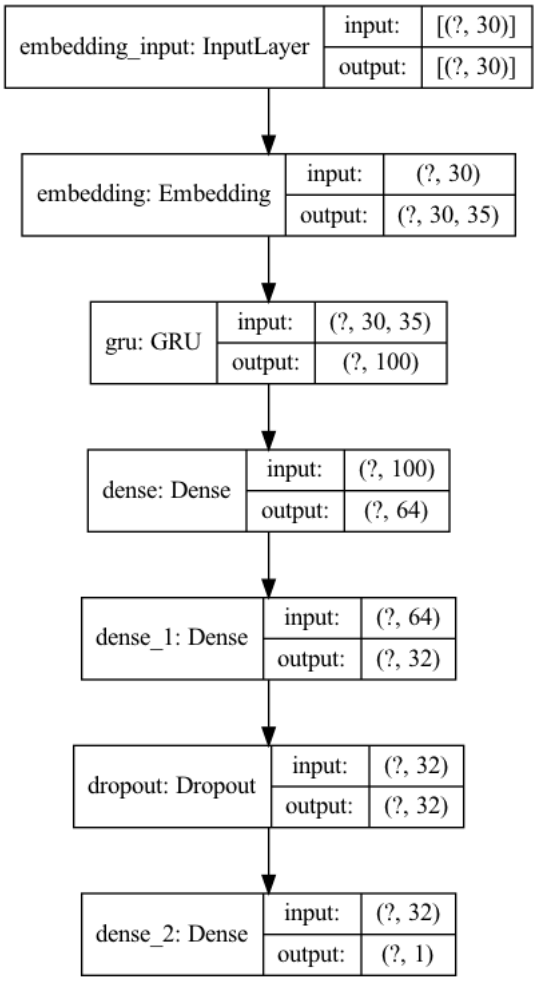


In [33]:
```
fig = plt.subplots(figsize=(12,8))
plt.plot(r.history['mae'], label='mae')
plt.plot(r.history['val_mae'], label='val_mae')
plt.title("Loss vs val Loss for RNN model on titles (MAE)", fontsize=15)
plt.xlabel("epochs", fontsize=15)
plt.ylabel("loss (mean absolute error)", fontsize=15)
plt.legend();
plt.savefig('images/RNN_GRU_MAE1.png')
```



In [34]:
```
plot_model(model,show_shapes=True, to_file='images/RNN_GRU1_arc.png')
```

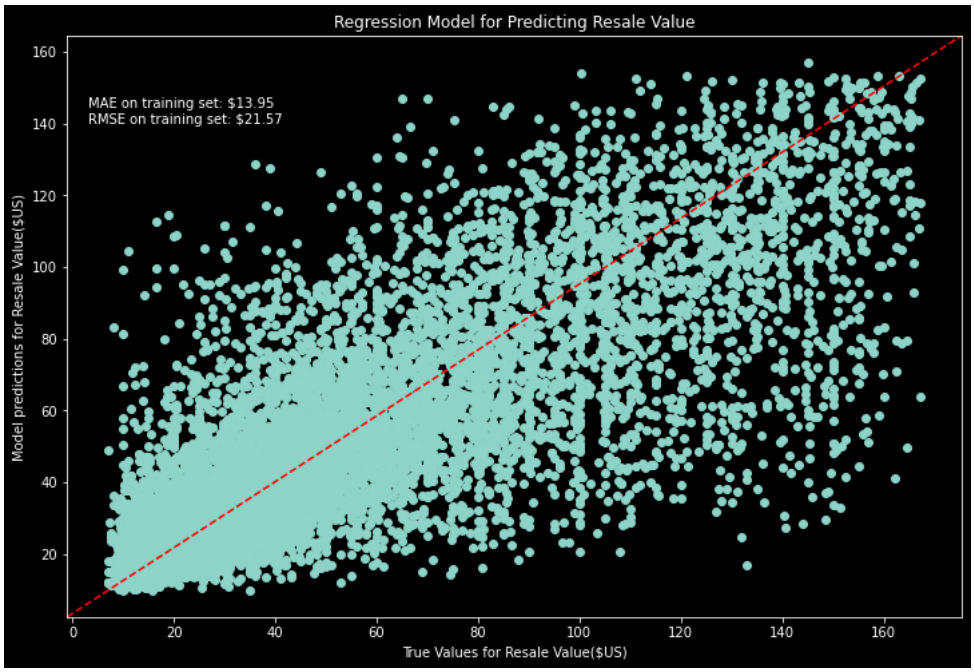
Out[34]:



In [35]:
```
test_mae = mean_absolute_error(Y_test, pred)
```

In [36]:
```
RMSE = np.sqrt(test_results[0])
```

In [37]:
```
string_score = f'\nMAE on training set: ${test_mae:.2f}'
string_score += f'\nRMSE on training set: ${RMSE:.2f}'
fig, ax = plt.subplots(figsize=(12, 8))
plt.scatter(Y_test, pred)
ax.plot([0, 1], [0, 1], transform=ax.transAxes, ls="--", c="red")
plt.text(3, 140, string_score)
plt.title('Regression Model for Predicting Resale Value')
plt.ylabel('Model predictions for Resale Value($US)')
plt.xlabel('True Values for Resale Value($US)')
plt.savefig('images/regression_GRU_relu1.png');
```



In [38]:
```
df_title['labels'].describe()
```

Out[38]:
```
count    78330.000000
mean        50.044127
std         36.026730
min          6.940000
25%         22.182500
50%         38.740000
75%         67.490000
max        167.490000
Name: labels, dtype: float64
```

In [39]:
```
df_title = df.loc[:, ['title', 'converted_price']]


df_title.rename({'title': 'data',
                 'converted_price': 'labels'},
                axis=1, inplace=True)
```

In [40]:
```
# df_title['labels'] = (df_title['labels']/mean_price)
Y = df_title['labels'].values
```

In [41]:
```
df_train, df_test, Ytrain, Ytest = train_test_split(df_title['data'],
                                                    Y,
                                                    test_size=0.3,
                                                    random_state=42)
```

In [42]:
```
X_val, X_test, Y_val, Y_test = train_test_split(df_test,
                                                Ytest,
                                                test_size=0.5,
                                                random_state=42)
```

LSTM

In [43]:
```
# Convert sentences to sequences
MAX_VOCAB_SIZE = 25000
tokenizer = Tokenizer(num_words=MAX_VOCAB_SIZE)
tokenizer.fit_on_texts(df_train)
sequences_train = tokenizer.texts_to_sequences(df_train)
sequences_val = tokenizer.texts_to_sequences(X_val)
sequences_test = tokenizer.texts_to_sequences(X_test)
```

In [44]:
```
# get word -> integer mapping
word2idx = tokenizer.word_index
V = len(word2idx)
print('Found %s unique tokens.' % V)
```

```
Found 32753 unique tokens.
```

In [45]:
```
# pad sequences so that we get a N x T matrix
data_train = pad_sequences(sequences_train)
print('Shape of data train tensor:', data_train.shape)

# get sequence length
T = data_train.shape[1]
```

```
Shape of data train tensor: (54831, 41)
```

In [46]:
```
data_val = pad_sequences(sequences_val, maxlen=T)
print('Shape of data test tensor:', X_val.shape)
```

```
Shape of data test tensor: (11749,)
```

In [47]:
```
data_test = pad_sequences(sequences_test, maxlen=T)
print('Shape of data test tensor:', X_test.shape)
```

```
Shape of data test tensor: (11750,)
```

In [48]:
```
# Create the RNN model
# We get to choose embedding dimensionality
D = 30
# Hidden state dimensionality
M = 35
i = Input(shape=(T,))
x = Embedding(V + 1, D)(i)
x = LSTM(M, return_sequences=True)(x)
x = GlobalMaxPooling1D()(x)
x = Dense(62, activation='relu')(x)
x = Dense(32, activation='relu')(x)
x = Dropout(0.3)(x)
x = Dense(1, activation='relu')(x)
model = Model(i, x)
```

In [49]:
```
# Compile and fit
model.compile(
  loss='MSE',
  optimizer='adam',
  metrics=['mae']
)


print('Training model...')
r = model.fit(
  data_train,
  Ytrain,
  epochs=5,
  validation_data=(data_val, Y_val)
)
```

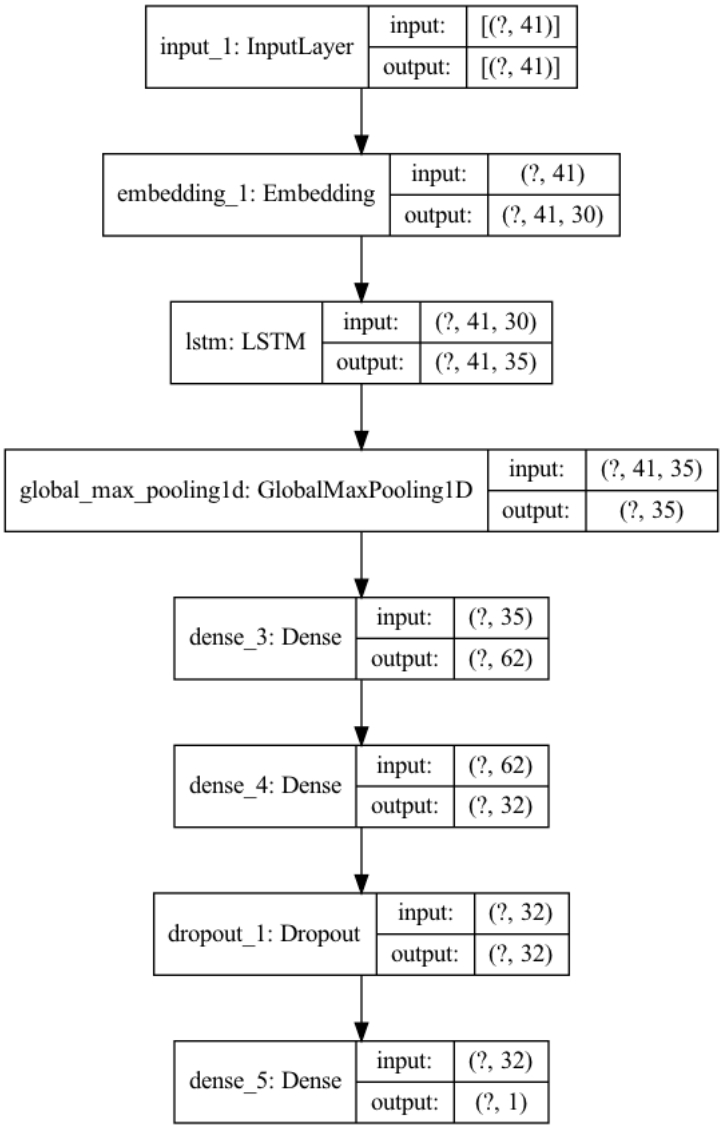
```
Training model...
Epoch 1/5
1714/1714 [==============================] - 25s 15ms/step - loss: 1026.4459 - mae: 23.0135 - val_loss: 539.7323 - va
l_mae: 16.0943
Epoch 2/5
1714/1714 [==============================] - 24s 14ms/step - loss: 581.2591 - mae: 16.6714 - val_loss: 482.6658 - val
_mae: 14.6322
Epoch 3/5
1714/1714 [==============================] - 24s 14ms/step - loss: 490.1191 - mae: 15.1249 - val_loss: 455.9258 - val
_mae: 14.2108
Epoch 4/5
1714/1714 [==============================] - 24s 14ms/step - loss: 439.0449 - mae: 14.2941 - val_loss: 439.0598 - val
_mae: 13.8696
Epoch 5/5
1714/1714 [==============================] - 24s 14ms/step - loss: 404.6346 - mae: 13.6278 - val_loss: 442.9078 - val
_mae: 13.9808
```

In [50]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 41, 30)            982620
_________________________________________________________________
lstm (LSTM)                  (None, 41, 35)            9240
_________________________________________________________________
global_max_pooling1d (Global (None, 35)                0
_________________________________________________________________
dense_3 (Dense)              (None, 62)                2232
_________________________________________________________________
dense_4 (Dense)              (None, 32)                2016
_________________________________________________________________
dropout_1 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 33
=================================================================
Total params: 996,141
Trainable params: 996,141
Non-trainable params: 0
_________________________________________________________________
```

In [51]:
```
plot_model(model,show_shapes=True, to_file='images/RNN_LSTM_arc.png')
```

Out[51]:



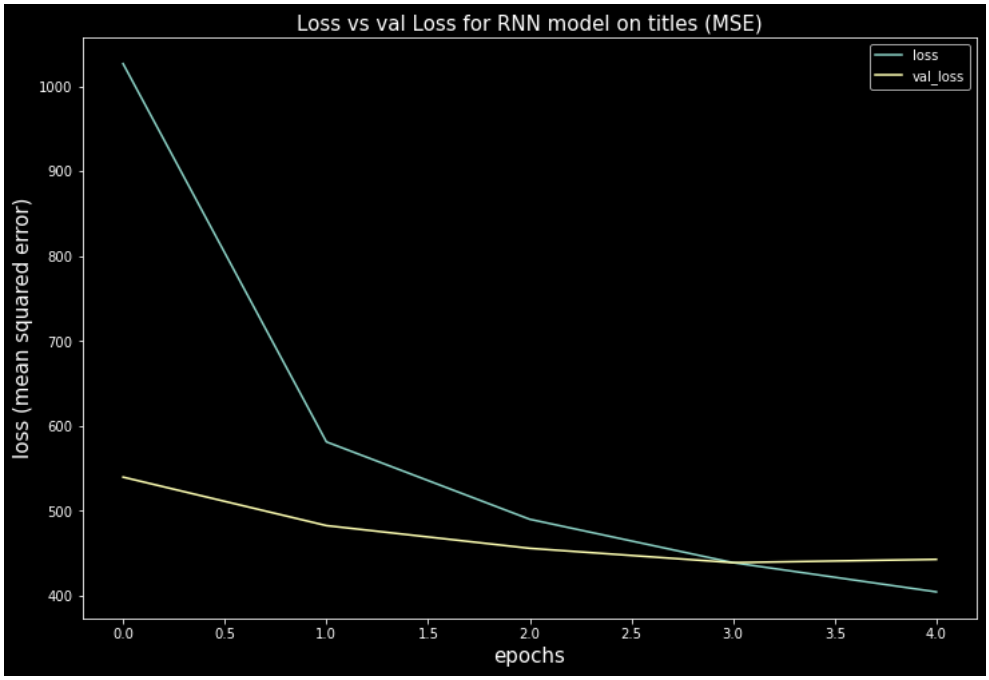
In [52]:
```
pred=model.predict(data_test)
```

In [53]:
```
test_results = model.evaluate(data_test, Y_test)
```

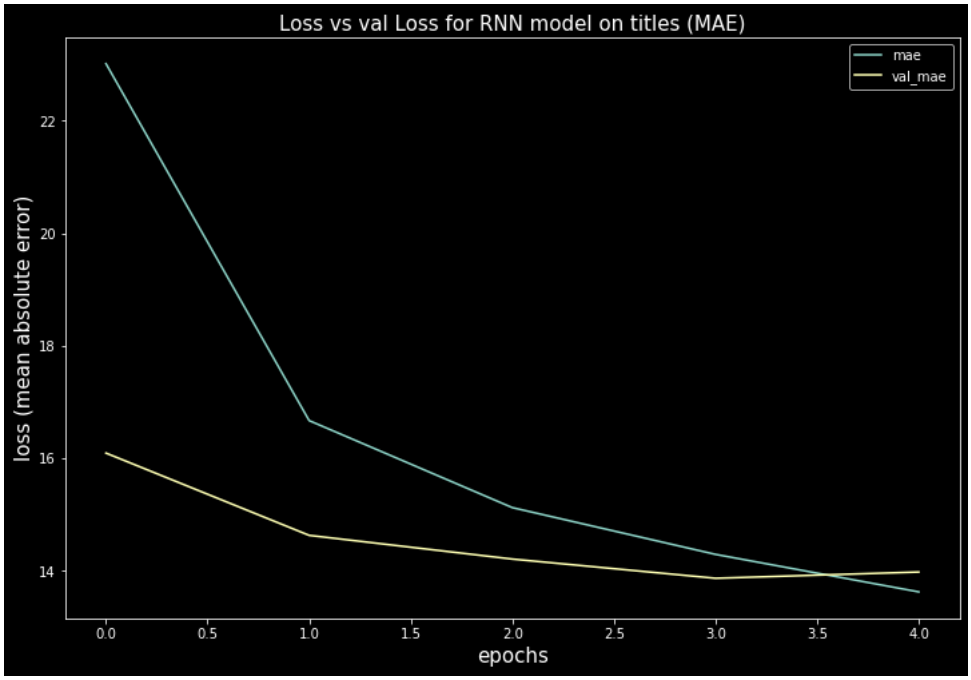
```
368/368 [==============================] - 1s 3ms/step - loss: 436.1495 - mae: 13.9282
```

In [54]:
```
RMSE = np.sqrt(test_results[0])
```

In [55]:
```
fig = plt.subplots(figsize=(12,8))
plt.plot(r.history['loss'], label='loss')
plt.plot(r.history['val_loss'], label='val_loss')
plt.title("Loss vs val Loss for RNN model on titles (MSE)", fontsize=15)
plt.xlabel("epochs", fontsize=15)
plt.ylabel("loss (mean squared error)", fontsize=15)
plt.legend()
plt.savefig('images/MSE_LSTM_relu.png');
```

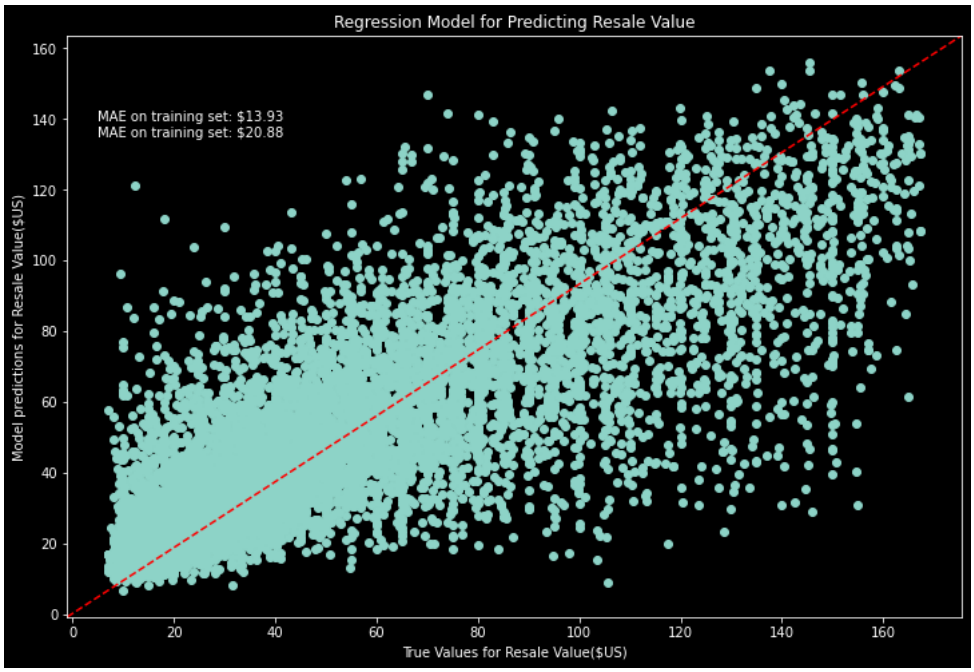


In [56]:
```
fig = plt.subplots(figsize=(12,8))
plt.plot(r.history['mae'], label='mae')
plt.plot(r.history['val_mae'], label='val_mae')
plt.title("Loss vs val Loss for RNN model on titles (MAE)", fontsize=15)
plt.xlabel("epochs", fontsize=15)
plt.ylabel("loss (mean absolute error)", fontsize=15)
plt.legend()
plt.savefig('images/MAE_LSTM_relu.png');
```



In [57]:
```
test_mae = mean_absolute_error(Y_test, pred)
```

In [58]:
```
string_score = f'\nMAE on training set: ${test_mae:.2f}'
string_score += f'\nMAE on training set: ${RMSE:.2f}'
fig, ax = plt.subplots(figsize=(12, 8))
plt.scatter(Y_test, pred)
ax.plot([0, 1], [0, 1], transform=ax.transAxes, ls="--", c="red")
plt.text(5, 135, string_score)
plt.title('Regression Model for Predicting Resale Value')
plt.ylabel('Model predictions for Resale Value($US)')
plt.xlabel('True Values for Resale Value($US)')
plt.savefig("images/regression_LSTM_relu.png")
```



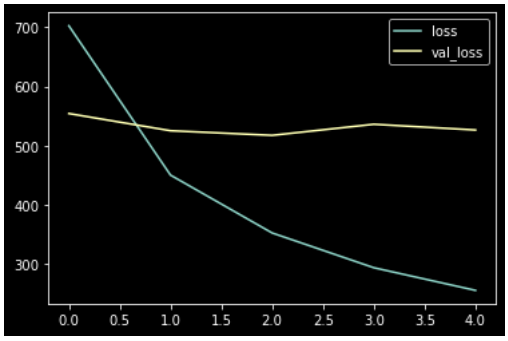
CNN Titles

In [59]:
```
# Create the CNN model

# We get to choose embedding dimensionality
D = 256



i = Input(shape=(T,))
x = Embedding(V + 1, D)(i)
x = Conv1D(32, 3, activation='relu')(x)
x = MaxPooling1D(3)(x)
x = Conv1D(64, 3, activation='relu')(x)
x = MaxPooling1D(3)(x)
x = Conv1D(128, 3, activation='relu')(x)
x = GlobalMaxPooling1D()(x)
x = Dense(1, activation='relu')(x)

model = Model(i, x)
```

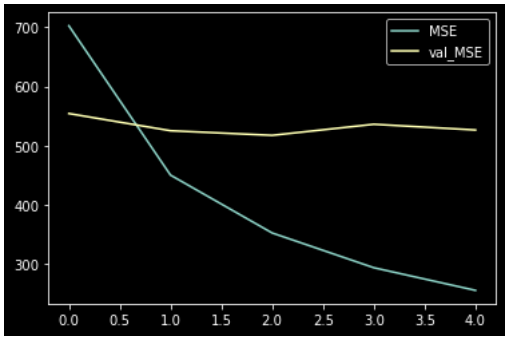
In [60]:
```
# Compile and fit
model.compile(
  loss='MSE',
  optimizer='adam',
  metrics=['mae']
)


print('Training model...')
r = model.fit(
  data_train,
  Ytrain,
  epochs=5,
  validation_data=(data_val, Y_val)
)

```

```
Training model...
Epoch 1/5
1714/1714 [==============================] - 79s 46ms/step - loss: 702.6185 - mae: 18.8140 - val_loss: 554.2573 - val
_mae: 16.6334
Epoch 2/5
1714/1714 [==============================] - 83s 48ms/step - loss: 450.1896 - mae: 14.6215 - val_loss: 525.1744 - val
_mae: 15.6066
Epoch 3/5
1714/1714 [==============================] - 79s 46ms/step - loss: 352.3939 - mae: 12.7084 - val_loss: 517.3931 - val
_mae: 15.5277
Epoch 4/5
1714/1714 [==============================] - 79s 46ms/step - loss: 293.6541 - mae: 11.4138 - val_loss: 536.0966 - val
_mae: 15.3805
Epoch 5/5
1714/1714 [==============================] - 80s 47ms/step - loss: 255.3643 - mae: 10.5055 - val_loss: 526.4434 - val
_mae: 15.5761
```

In [61]:
```
# Plot loss per iteration
import matplotlib.pyplot as plt
plt.plot(r.history['loss'], label='loss')
plt.plot(r.history['val_loss'], label='val_loss')
plt.legend();
```



In [64]:
```
# Plot accuracy per iteration
plt.plot(r.history['loss'], label='MSE')
plt.plot(r.history['val_loss'], label='val_MSE')
plt.legend();
```



CNN using images as input

In [65]:
```
df_imgs = df.drop(['title', 'url',
                   'date_sold', 'profit',
                   'ROI', 'brand', 'cost',
                   'pictureURLLarge'],
                    axis=1).copy()
```

In [66]:
```
df_imgs.dropna(subset=['Image'], inplace=True)
```

In [67]:
```
df_imgs.reset_index(drop=True, inplace=True)
```

In [68]:
```
df_imgs['file_index'] = df_imgs.index.values
df_imgs['file_index'] = df_imgs['file_index'].astype(str)
```

In [69]:
```
df_imgs['filename'] = df_imgs['file_index'] + '.jpg'
```

In [70]:
```
def download(row):
    filename = row.filepath

# create folder if it doesn't exist
#     os.makedirs(os.path.dirname(filename), exist_ok=True)

    url = row.Image
#     print(f"Downloading {url} to {filename}")

    try:
        r = requests.get(url, allow_redirects=True)
        with open(filename, 'wb') as f:
            f.write(r.content)
    except:
        print(f'{filename} error')
```

In [71]:
```
root_folder = 'C:/Users/12108/Documents/GitHub/Neural_Network_Predicting_Reseller_Success_Ebay/nn_images/'
df_imgs['filepath'] = root_folder + df_imgs['filename']
```

In [72]:
```
df_imgs['filepath'].sample(2).apply(print)
```

```
C:/Users/12108/Documents/GitHub/Neural_Network_Predicting_Reseller_Success_Ebay/nn_images/74992.jpg
C:/Users/12108/Documents/GitHub/Neural_Network_Predicting_Reseller_Success_Ebay/nn_images/12140.jpg
```

Out[72]:
```
74992    None
12140    None
Name: filepath, dtype: object
```

In [73]:
```
# df_imgs.apply(download, axis=1)
```

All image files are stored locally for this project. The below markdown code is for reference.

```
img_list = os.listdir('C:/Users/12108/Documents/GitHub/Neural_Network_Predicting_Reseller_Success_Ebay/nn_image
s/')

img_df = df_imgs.loc[df_imgs['filename'].isin(img_list)].copy()

img_df.reset_index(drop=True, inplace=True)



img_df.rename({'Image': 'data',
               'converted_price': 'labels'},
                axis=1, inplace=True)
```

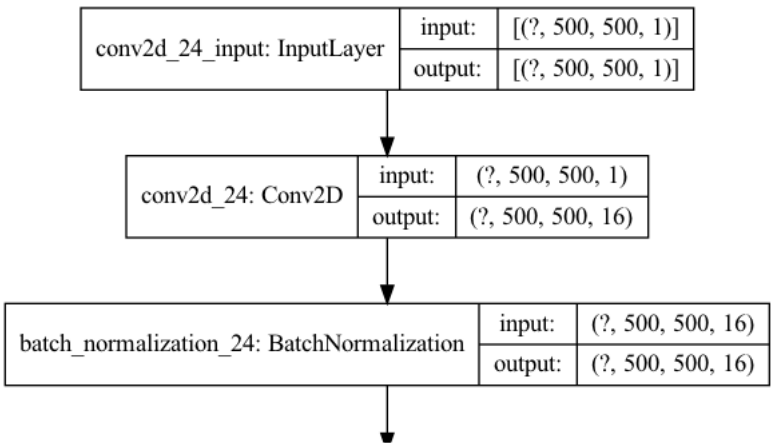
```
df_train, df_test, Ytrain, Ytest = train_test_split(img_df, Y, test_size=0.20)
datagen=ImageDataGenerator(rescale=1./255.,validation_split=0.20)

train_generator=datagen.flow_from_dataframe(
dataframe=df_train,
directory= None,
x_col="filepath",
y_col="labels",
subset="training",
batch_size=100,
seed=55,
shuffle=True,
class_mode="raw")

valid_generator=datagen.flow_from_dataframe(
dataframe=df_train,
directory=None,
x_col="filepath",
y_col="labels",
subset="validation",
batch_size=100,
seed=55,
shuffle=True,
class_mode="raw")

test_datagen=ImageDataGenerator(rescale=1./255.)
test_generator=test_datagen.flow_from_dataframe(
dataframe=df_test,
directory=None,
x_col="filepath",
y_col="labels",
batch_size=100,
seed=55,
shuffle=False,
class_mode="raw")
```

In [74]:
```
# model = models.Sequential()

# model.add(layers.Conv2D(16, (3, 3), padding='same', activation='relu',
#                         input_shape=(256 ,256,  3)))
# model.add(layers.BatchNormalization())
# model.add(layers.Conv2D(16, (3, 3), activation='relu', padding='same'))
# model.add(layers.BatchNormalization())
# model.add(layers.MaxPooling2D((2, 2)))

# model.add(layers.Conv2D(32, (3, 3), padding='same', activation='relu',
#                         input_shape=(256 ,256,  3)))
# model.add(layers.BatchNormalization())
# model.add(layers.Conv2D(32, (3, 3), activation='relu', padding='same'))
# model.add(layers.BatchNormalization())
# model.add(layers.MaxPooling2D((2, 2)))

# model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))
# model.add(layers.BatchNormalization())
# model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))
# model.add(layers.BatchNormalization())
# model.add(layers.MaxPooling2D((2, 2)))

# model.add(layers.Conv2D(128, (3, 3), activation='relu', padding='same'))
# model.add(layers.BatchNormalization())
# model.add(layers.Conv2D(128, (3, 3), activation='relu', padding='same'))
# model.add(layers.BatchNormalization())
# model.add(layers.MaxPooling2D((2, 2)))

# model.add(layers.Flatten())

# model.add(Dense(512, activation='relu'))
# model.add(Dropout(0.1))
# model.add(Dense(256, activation='relu'))
# model.add(Dropout(0.1))
# model.add(Dense(128, activation='relu'))
# model.add(Dense(1, activation='linear'))

# model.compile(loss='MSE',
#               optimizer='Adam',
#                metrics=['mae', 'mse'])

# summary = model.fit(train_generator, epochs=3, validation_data=valid_generator)
```

In [75]:
```
model = tf.keras.models.load_model('cnn_grayscale_relu1.h5',  compile=False)
```

In [76]:
```
plot_model(model, show_shapes=True, to_file="images/CNN_architecture.png")
```

Out[76]:



In [77]:
```
model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_24 (Conv2D)           (None, 500, 500, 16)      160
_________________________________________________________________
batch_normalization_24 (Batc (None, 500, 500, 16)      64
_________________________________________________________________
max_pooling2d_16 (MaxPooling (None, 250, 250, 16)      0
_________________________________________________________________
conv2d_25 (Conv2D)           (None, 250, 250, 32)      4640
_________________________________________________________________
batch_normalization_25 (Batc (None, 250, 250, 32)      128
_________________________________________________________________
max_pooling2d_17 (MaxPooling (None, 125, 125, 32)      0
_________________________________________________________________
conv2d_26 (Conv2D)           (None, 125, 125, 64)      18496
_________________________________________________________________
batch_normalization_26 (Batc (None, 125, 125, 64)      256
_________________________________________________________________
max_pooling2d_18 (MaxPooling (None, 62, 62, 64)        0
_________________________________________________________________
conv2d_27 (Conv2D)           (None, 62, 62, 128)       73856
_________________________________________________________________
batch_normalization_27 (Batc (None, 62, 62, 128)       512
_________________________________________________________________
max_pooling2d_19 (MaxPooling (None, 31, 31, 128)       0
_________________________________________________________________
flatten_4 (Flatten)          (None, 123008)            0
_________________________________________________________________
dense_12 (Dense)             (None, 512)               62980608
_________________________________________________________________
dense_13 (Dense)             (None, 128)               65664
_________________________________________________________________
dense_14 (Dense)             (None, 1)                 129
=================================================================
Total params: 63,144,513
Trainable params: 63,144,033
Non-trainable params: 480
_________________________________________________________________
```

In [ ]:
```
model.evaluate(valid_generator)
```

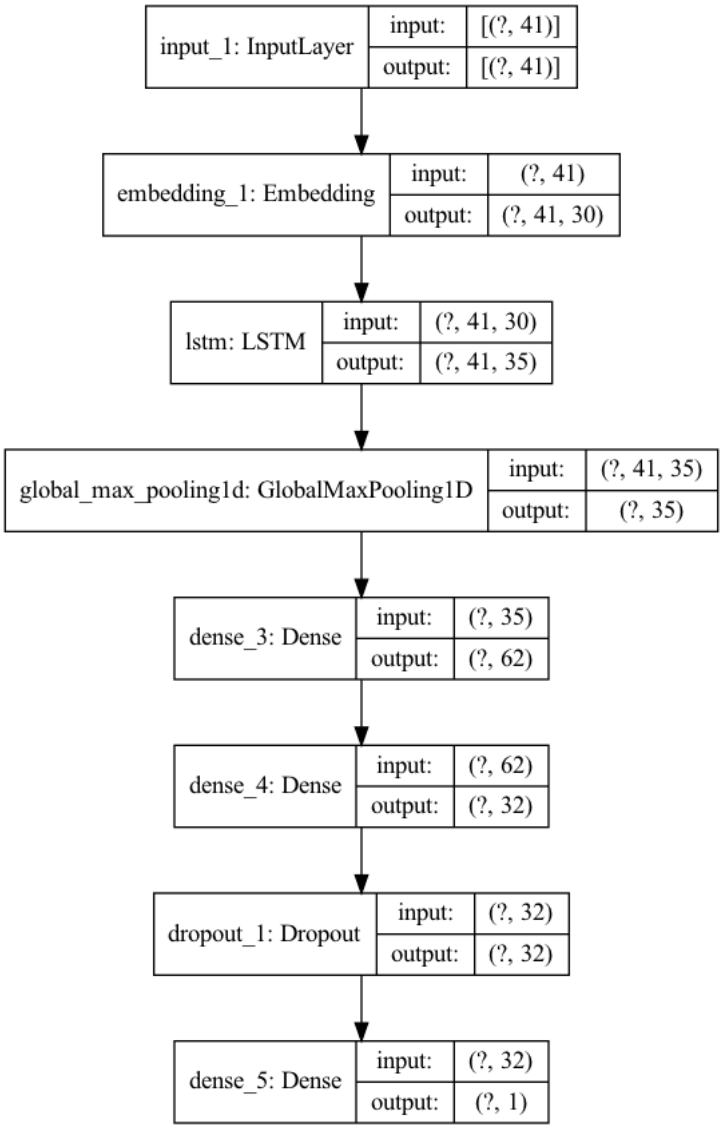
In [ ]:
```
test_generator.reset()
pred=model.predict(test_generator,verbose=1)
```

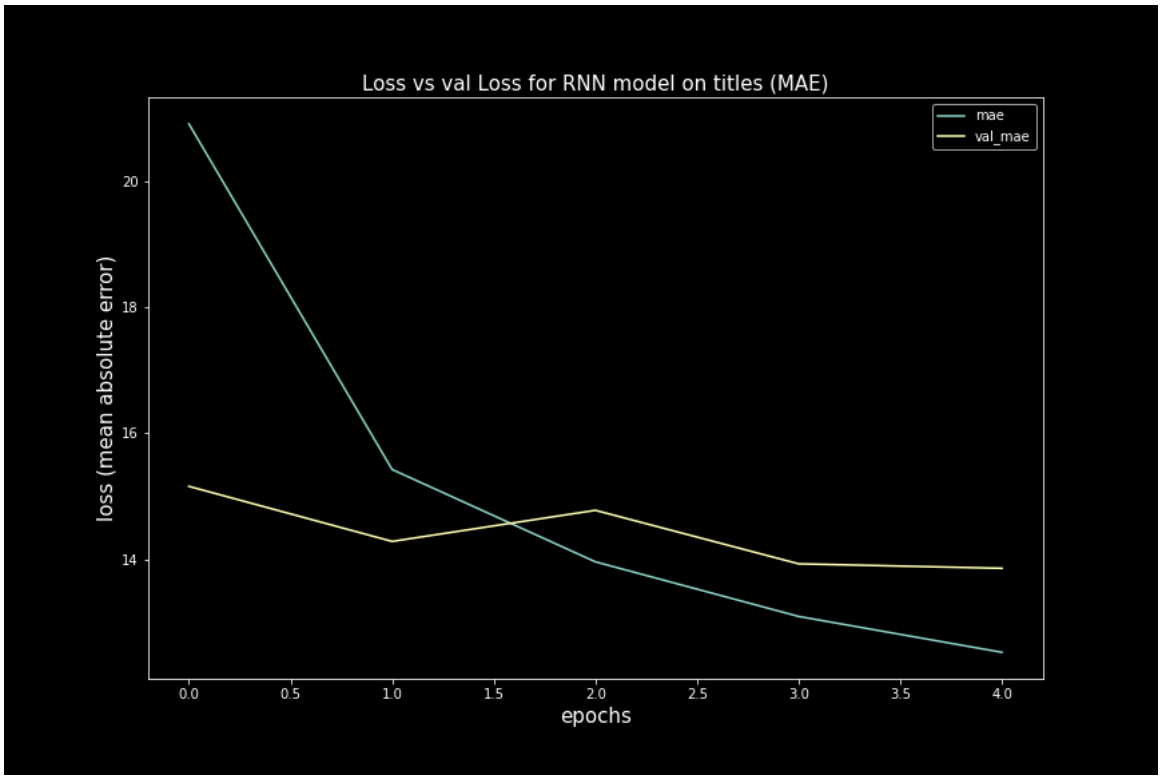
In [ ]:
```
test_results = model.evaluate(test_generator)
```

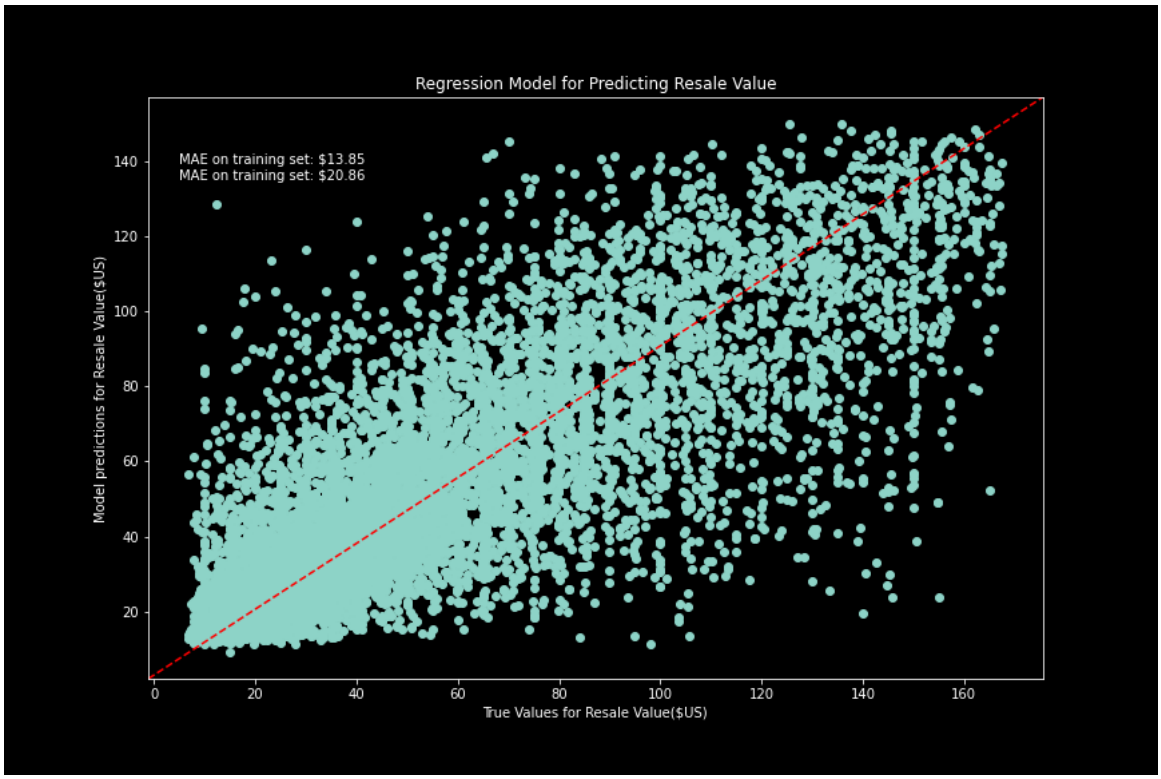
In [ ]:
```
fig = plt.figure(figsize=(12,8))
plt.plot(summary.history['loss'])
plt.plot(summary.history['val_loss'])
plt.plot
plt.title('model loss')
plt.ylabel('loss(mean absolute error)')
plt.xlabel('epoch')
plt.legend(['train_loss', 'val_loss'], loc='upper right')
plt.show();
```

Results

Recurrent Neural Network (Long Short Term Memory)

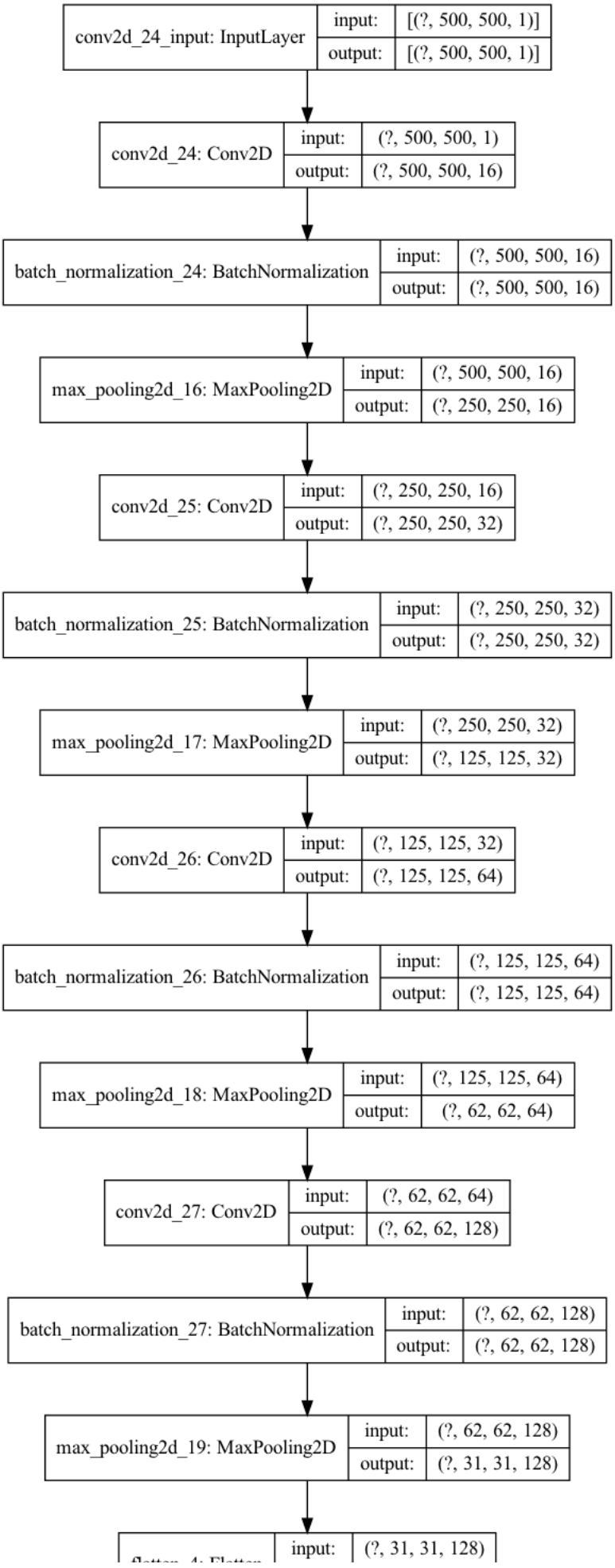


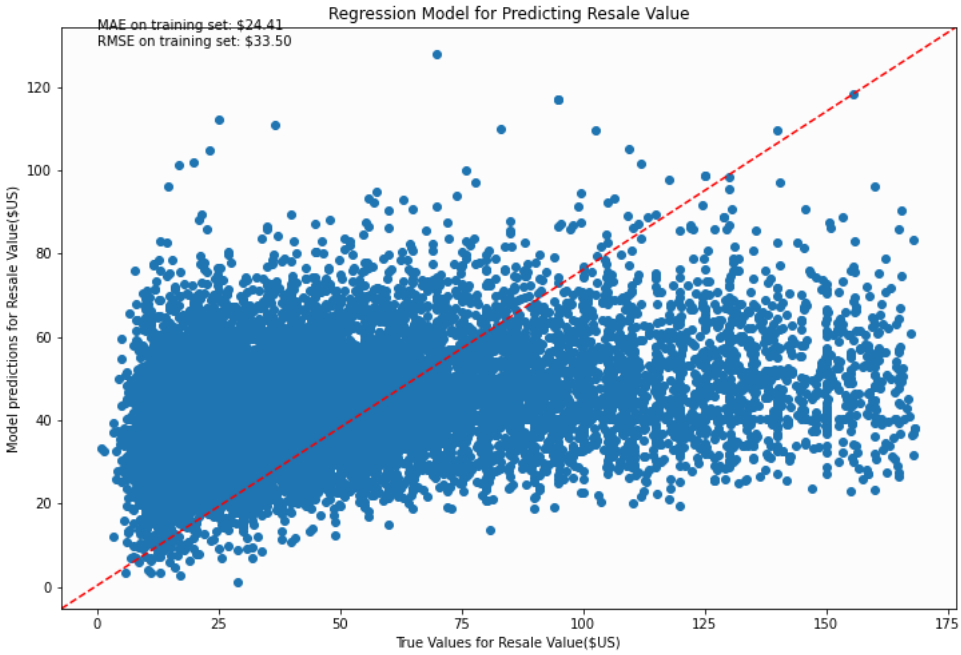


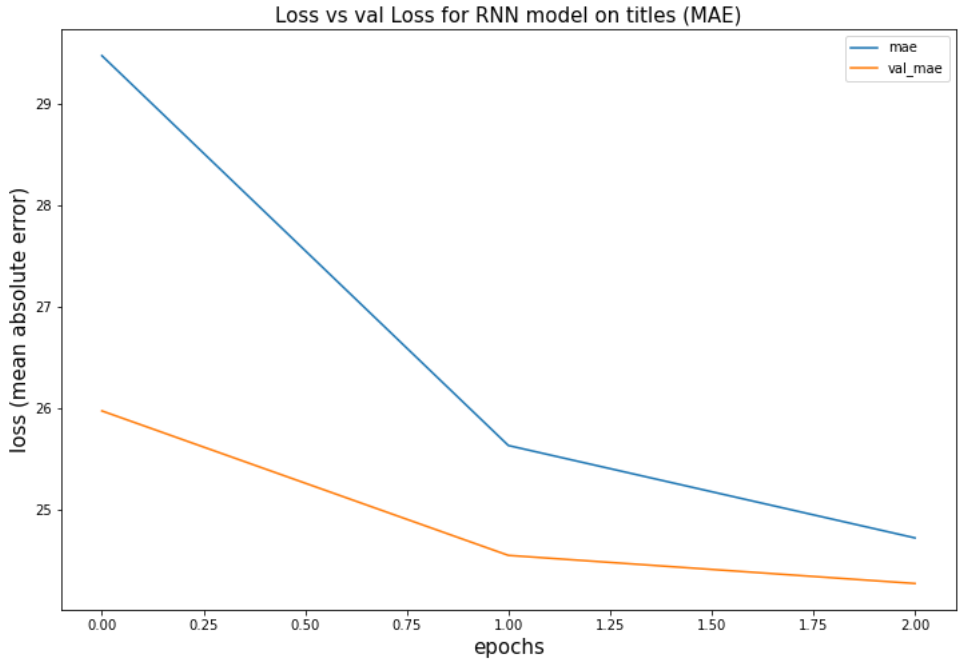


- The mean price of the 8 brands of knives sold on ebay is around $50.00. A mean absolute error of about plus or minus $13.80 is acceptable.

Convoluted Neural Network on Grayscale Images


conv2d_24_input: InputLayer
input: [(?, 500, 500, 1)]
output: [(?, 500, 500, 1)]
conv2d_24: Conv2D
input: (?, 500, 500, 1)
output: (?, 500, 500, 16)
batch_normalization_24: BatchNormalization
input: (?, 500, 500, 16)
output: (?, 500, 500, 16)
max_pooling2d_16: MaxPooling2D
input: (?, 500, 500, 16)
output: (?, 250, 250, 16)
conv2d_25: Conv2D
input: (?, 250, 250, 16)
output: (?, 250, 250, 32)
batch_normalization_25: BatchNormalization
input: (?, 250, 250, 32)
output: (?, 250, 250, 32)
max_pooling2d_17: MaxPooling2D
input: (?, 250, 250, 32)
output: (?, 125, 125, 32)
conv2d_26: Conv2D
input: (?, 125, 125, 32)
output: (?, 125, 125, 64)
batch_normalization_26: BatchNormalization
input: (?, 125, 125, 64)
output: (?, 125, 125, 64)
max_pooling2d_18: MaxPooling2D
input: (?, 125, 125, 64)
output: (?, 62, 62, 64)
conv2d_27: Conv2D
input: (?, 62, 62, 64)
output: (?, 62, 62, 128)
batch_normalization_27: BatchNormalization
input: (?, 62, 62, 128)
output: (?, 62, 62, 128)
max_pooling2d_19: MaxPooling2D
input: (?, 62, 62, 128)
output: (?, 31, 31, 128)
input: (?, 31, 31, 128)





- The MAE when testing the CNN was roughly $25.00. That is an error of plus or minus about 50% of the mean price of knives sold. Not acceptable yet as compared to the RNN with titles. Will address in future work.

Future Work

- Expand data to include other products readily purchasable at the Surplus Store.
- Attempt data augmentation on the CNN image network
- Attempt to obtain more aspect data for sold knives. Some important aspect data is limited access to sellers who average a certain amount of money per month.

In [ ]:
```
# # define two sets of inputs
# inputA = Input(shape=(32,))
# inputB = Input(shape=(128,))
# # the first branch operates on the first input
# x = Dense(8, activation="relu")(inputA)
# x = Dense(4, activation="relu")(x)
# x = Model(inputs=inputA, outputs=x)
# # the second branch opreates on the second input
# y = Dense(64, activation="relu")(inputB)
# y = Dense(32, activation="relu")(y)
# y = Dense(4, activation="relu")(y)
# y = Model(inputs=inputB, outputs=y)
# # combine the output of the two branches
# combined = concatenate([x.output, y.output])
# # apply a FC layer and then a regression prediction on the
# # combined outputs
# z = Dense(2, activation="relu")(combined)
# z = Dense(1, activation="linear")(z)
# # our model will accept the inputs of the two branches and
# # then output a single value
# model = Model(inputs=[x.input, y.input], outputs=z)
```

In [ ]:
```

```